

# Uncertainty and the Shadow Banking Crisis: A Structural Estimation\*

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December 8, 2016

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\*I would like to thank Yan Bai, Toni Whited, George Alessandria, Dan Lu, Tommaso Mancini-Griffoli, Robert Ready, Olga Itenberg, Dong Beom Choi, Ryan Michaels, Vincenzo Quadrini, Ivan Werning, Mark Bills, Yongsung Chang, Yena Park, Josh Kinsler, Bin Chen, Stephan Danninger, Jianping Qi, Gabriel Mihalache, Tuo Deng, David Slichter, Yicheng Wang and Tiago Tavares for their great comments and encouragement. I would also like to thank discussants and other participants in the Midwest Macro Meeting 2015, Georgetown Economics Research Center Biennial Conference(GCER) 2015, Money, Macro and Finance Conference 2015, FMA 2015 Annual Meeting, Financial Intermediation Research Society Conference(FIRS) 2016, Royal Economic Society PhD meeting 2016, and seminar participants at the University of Rochester, Bank of Canada, University of Toronto, Georgetown University, Temple University, Peking University, Baylor University, and the International Monetary Fund for their helpful comments and discussions. Special thanks to Center for Integrated Research Computing(CIRC) at the University of Rochester and the Stampede-Texas Advanced Computing Center(TACC) for computational support. All remaining errors are my own. Contact Information: Xu Tian, 150 St. George Street, University of Toronto, Toronto, Ontario, M5S 3G7. Email: [xu.tian@utoronto.ca](mailto:xu.tian@utoronto.ca).

# Uncertainty and the Shadow Banking Crisis: A Structural Estimation

## Abstract

Shadow banks play an important role in the modern financial system and are arguably the source of key vulnerabilities leading to the 2007-2009 financial crisis. In this paper, I develop a quantitative framework with endogenous bank default and aggregate uncertainty fluctuation to study the dynamics of shadow banking. I argue that the increase in asset return uncertainty during the crisis results in the spread spike, making it more costly for shadow banks to roll over their debt in the short-term debt market. As a result, these banks are forced to deleverage, leading to a decrease in the credit supply. The model is estimated using a bank-level dataset of shadow banks in the United States. The findings show that uncertainty shocks are able to generate statistics and pathways of leverage, spread, and assets which closely match those observed in the data. Maturity mismatch and asset fire-sales amplify the impact of the uncertainty shocks. First-moment shocks alone can not reproduce the large interbank spread spike, dramatic deleveraging and contraction of the U.S. shadow banking sector during the crisis. The model also allows for policy experiments. I analyze how unconventional monetary policies can help to counter the rise in the interbank spread, thus stabilizing the credit supply. Taking into consideration of bank moral hazard, I find that government bailout might be counterproductive as it might result in more aggressive risk-taking of shadow banks.

**Keywords:** Shadow banking, uncertainty, maturity mismatch, fire-sale, unconventional monetary policy, moral hazard.

**JEL Classification:** D81, E32, E44, E50, G18, G20.

The 2007-2009 financial crisis is distinguished from previous crises by the role played by the shadow banking sector. Shadow banks are financial intermediaries that conduct maturity, credit, and liquidity transformation without explicit access to central bank liquidity or public sector credit guarantees. They play a major role in global finance and are arguably the source of key vulnerabilities leading to the recent crisis. Different from traditional banks whose funding mainly depends on customer deposits, shadow banks finance their asset purchases primarily by means of collateralized debt with very short maturity, such as repurchase agreements (repo) or asset-backed commercial papers (ABCP). The markets for these financial instruments are typically highly liquid. However, during the recent financial crisis, the initial loss of some of the assets (mainly subprime mortgage-backed security) which serve as collateral in the repo or ABCP transactions<sup>1</sup>, together with the uncertainty surrounding individual exposures to such assets, led financial institutions to largely stop exchanging liquidities in these markets. Interbank spread spiked up and market liquidity shrank dramatically, forcing the shadow banks to deleverage and ultimately resulting in a contraction in the credit intermediation.

In this paper, I develop a quantitative model with endogenous bank default and aggregate uncertainty fluctuation to explain the increase of interbank spread and the contraction of shadow banking credit intermediation during the recent financial crisis. The increase in bank asset return uncertainty raises the bank default probability, leading to an increase in the interbank market spread<sup>2</sup>. Facing a higher cost of financing, banks are forced to deleverage, thus decreasing the credit intermediation. Using this framework, I also analyze how unconventional monetary policy (debt guarantees and the Trouble Asset Relief Program) can help to reduce the interbank spread and stimulate the supply of credit. Assuming bailout probability is an increasing function of bank sizes, I also show that bank bailouts might worsen moral hazard. Bigger banks might think they are “too big to fail” and would be bailed out by the government with higher probability. Thus they would take excessive risk and act less responsibly.

The contribution of this paper is both empirical and theoretical. Using a comprehensive bank-level dataset, I find that during the 2007-2009 financial crisis, the asset return uncertainty of shadow banks

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<sup>1</sup>Covitz, Liang, and Suarez (2014) argue that contraction in the asset-backed commercial paper (ABCP) market played a central role in transforming concerns about the credit quality of mortgage-related assets into a global financial crisis.

<sup>2</sup>Since the major participants in the short-term collateralized debt market are financial institutions, in this paper, I use the term “interbank market” and “short-term collateralized debt market” interchangeably. See Pozsar, Adrian, Ashcraft, and Boesky (2013) for an in-depth analysis about shadow banking and short-term collateralized debt markets.

increased by 147%; they deleveraged much more than traditional banks and shrank their asset size by 21%. Moreover, I decompose the change of aggregate leverage of shadow banks into two margins: the “intensive margin” and “extensive margin”<sup>3</sup>. I find that the “extensive margin” contributed more to the aggregate leverage changes of shadow banks than the “intensive margin”. I also find shadow banks depend heavily on short-term funding and tend to choose riskier asset portfolios compared with traditional banks. Surprisingly, to the best of my knowledge, I am the first to document these stylized facts of the U.S. shadow banking industry using a comprehensive micro-level dataset.

On the theoretical front, I first present a tractable two period framework illustrating the impact of uncertainty on the financing and leverage decisions of shadow banks. Then I extend the framework to an infinite horizon model with endogenous bank default and aggregate uncertainty fluctuation. In the model, shadow banks borrow from the interbank market using short-term risky debt and invest in a long-term risky loan<sup>4</sup>. In each period, every bank receives an idiosyncratic shock to its asset return. Depending on the realization of asset return and debt due, each bank decides whether to default<sup>5</sup>, how much new debt and equity to issue, new loans to invest in, and how much long-term asset to fire-sale (if necessary) to pay its debts due. I assume the idiosyncratic asset return shock is drawn from a log-normal distribution. When the standard deviation of the distribution increases, the bank’s asset return becomes riskier and its expected default probability would increase; thus it would be charged a higher interest rate in the interbank market. Facing a higher cost of financing and higher probability of costly asset fire-sales, shadow banks reduce their leverages and assets.

Using simulated method of moments (SMM), the model parameters are estimated to best fit a wide-ranging set of facts about the U.S. shadow banking industry, such as moments from the distribution of leverage, asset growth, default probability, and dividend payouts. Using the estimated parameters, I document the model’s implications for the shadow banking dynamics by conducting an event study about the 2007-2009 financial crisis and several counterfactual experiments in the spirit of recent microeconomic analyses. These out-of-sample tests reveal that uncertainty shocks are able

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<sup>3</sup>The intensive margin is the leverage change resulting from banks on all asset quantiles take lower leverage given a fixed asset distribution. Extensive margin is the leverage change resulting from the change of bank asset distribution. See stylized fact 4 in Section 1.2 for detailed definition of extensive and intensive margins.

<sup>4</sup>Assets and liabilities exhibit maturity mismatches, which is characteristic of the shadow banking industry. These institutions invest in long-term risky financial assets largely funded by short-term debt that must be rolled over frequently. The model is one of shadow banking instead of commercial banking because there is no government insurance present on any portion of the bank’s assets, nor is there any funding via deposits.

<sup>5</sup>In the model, the bank can default on its debt if its internal resources are insufficient to roll over its debt, so the interest rate on its debt is determined endogenously by a lender’s zero-profit condition.

to generate statistics and leverage, interest rate spread, and asset pathways that closely match the empirical observations about the U.S. shadow banking industry. In particular, when running the same regressions on the model-generated data, the coefficients estimate for the impact of the asset return uncertainty on shadow bank leverages is quantitatively similar to its empirical counterparts even though it is not targeted in the estimation. I also find that high maturity mismatch and firesale costs amplify the impact of uncertainty shocks. Alternative models with only pure first-moment shocks, without asset firesale costs, or without maturity mismatch, can not reproduce the large spike in the interbank spread, dramatic deleveraging, or contraction in the U.S. shadow banking industry in the recent financial crisis.

This paper contributes to the large literature on the shadow banking crisis. Following [Gorton and Metrick \(2012\)](#), who argue that the panic of 2007-2008 was a run on the short-term collateralized debt market, various studies have emphasized the role played by shadow banking sector in the origin and propagation of the financial turmoil. [Pozsar et al. \(2013\)](#) maintain that the shadow banking sector played a major role in the 2007-2009 financial crisis. [Krishnamurthy, Nagel, and Orlov \(2012\)](#) document how the collapse of the ABCP lead to the implosion of the intermediation chain within the shadow banking sector. [Adrian and Shin \(2010\)](#) argue that due to the limited liability of the short debt contracts of shadow banks, during the crisis, creditors in the interbank market are less willing to roll over their lending, resulting in the procyclicality of financial intermediaries' leverage and credit supply. [Chodorow-Reich \(2014\)](#) argues that the contraction of the credit supply matters more for the decline in output compared with the decrease of credit demand, and interbank market disruption played a crucial role in the decrease in the credit intermediation. [Schroth, Suarez, and Taylor \(2013\)](#) use the 2007 asset-backed commercial paper (ABCP) crisis as a laboratory to study the determinants of debt runs. [Corbae and D'Erasmus \(2014\)](#) develop a model of banking industry dynamics to study the relation between commercial bank market structure, entry and exit along the business cycle. The shocks in these papers are all first-moment shocks (TFP shocks or Investment quality shocks). Different from these papers, I focus on the impact of uncertainty shock (also called second-moment shocks) on the financing and leverage decisions of shadow banks. [Nuno and Thomas \(2014\)](#) also build a model to analyze the impact of uncertainty shocks on banks' leverage choices. They use log-linear approximations to study how financial frictions amplify shocks near the steady state of the economic system. This would only work if the economy is not knocked too far away

from the steady state. Compared with their work, my model characterizes the financial intermediary dynamics in a fully nonlinear manner. Such nonlinearities can generate rich and interesting dynamics. Also, in their model, bank default decisions are not endogenously determined, whereas my model allows for such a possibility. The literature on shadow banking is growing, however, existing literature either only studies the shadow banking activity empirically or focuses on commercial bank's behaviors using calibrated models<sup>6</sup>. To the best of my knowledge, no previous studies have used comprehensive micro-level shadow banking data to estimate the impacts of time-varying uncertainty and financial frictions in this sector. This paper fills the gap.

This paper is complementary to the growing literature studying the impact of uncertainty on the real economy, such as [Arellano, Bai, and Kehoe \(2012a\)](#), [Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry \(2012\)](#), [Christiano, Motto, and Rostagno \(2014\)](#) and [Gilchrist, Sim, and Zakrajsek \(2013\)](#). All these papers focus on the impact of uncertainty on non-financial firms' choice about investment or employment, whereas I focus on the decisions of financial intermediaries. In these papers, the marginal rate of substitution of financial intermediaries is often implicitly assumed to be equal to that of households or firms. Thus financial intermediaries always act on behalf of the households or firms and their decisions are often not modeled. However, one of the key features of the recent crisis is the disruption of financial intermediation. Without explicitly modeling the behaviors of financial institutions, we might not be able to fully understand the cause of this crisis.

Lastly, this paper is also related to the literature concerning interbank markets and unconventional monetary policy, such as [Gertler and Kiyotaki \(2010\)](#). Different from [Gertler and Kiyotaki \(2010\)](#), in my model, a bank's debt is risky and the bank might choose to default in equilibrium, whereas in [Gertler and Kiyotaki \(2010\)](#), interbank loans are fully collateralized and there is no default risk in the equilibrium. Moreover, in this strand of literature, crises are often driven by first-moment (levels) shocks such as investment quality shock, while I argue that even if the expected level of asset return shock remains unchanged, an increase in the uncertainty of asset return can result in the freeze of interbank market and the reduction in the supply of credit. Furthermore, I take into account the moral hazard behavior of shadow banks by endogenizing the bailout probability as a function of the

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<sup>6</sup>Calibration often only tries to match a few stylized facts with many model parameters, and whenever there are too many degrees of freedom, inference is impossible. In contrast, structural estimation matches at least as many stylized facts as model parameters, and therefore standard errors can be calculated in the same way as GMM standard error. It tries to find the unique set of model parameters that reconcile the model with the data. It is therefore an explicitly empirical exercise that attempts to "stress test" a single model to compare the performance of competing models. See [Strebulaev and Whited \(2012\)](#) for a detailed comparison of calibration and structural estimation.

bank size. Researchers have typically analyzed how credit policy can mitigate a credit crunch ex-post, or investigated the moral hazard of government bailout theoretically. This paper contributes to fill in this gap by developing a quantitative model to assess the interaction between ex-post interventions and the build-up of risk ex-ante in a tractable unified framework.

The paper is organized as follows. In Section 1, I document several stylized facts of the U.S. shadow banking industry. In Section 2, I illustrate the impact of uncertainty on the leverage and financing decisions of shadow banks using a two-period model, laying the theoretical groundwork for further quantitative exploration. In Sections 3 and 4, I analyze the shadow banking industry dynamics using an infinite horizon model with endogenous bank default and aggregate uncertainty fluctuation. Concluding remarks are given in Section 5.

## 1 Empirical Analysis

### 1.1 Data Source

In this section, I document several stylized facts about the U.S. banking industry. Since [Gorton and Metrick \(2012\)](#), there has been an outpouring of theoretical work on the shadow banking sector but the empirical work is only slowly catching up. I obtain yearly bank-level panel data from the BankScope and WorldScope databases. BankScope and WorldScope contain comprehensive information on financial institutions across the globe. I choose real estate and mortgage banks, investment banks, micro-financing institutions, securities firms, private banking and asset management companies, investment and trust corporations, finance companies, and group finance companies in the U.S. as representatives<sup>7</sup> of shadow banks<sup>8</sup>. I also choose commercial banks, savings banks, cooperative banks, and bank holding companies as representatives of traditional banks. The final panel data sample contains 281 shadow banks and 9554 traditional banks for the 1998 to 2013 period, covering 49 states in the U.S. As a robustness check, I also obtain quarterly aggregated data from the U.S. Flow of Funds Database. The sample periods are from 1990:Q1 to 2013:Q4.<sup>9</sup>

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<sup>7</sup>My classification of shadow banks is similar to the Financial Stability Board(FSB)'s measure of shadow banking activity based on nonbank financial intermediaries (NBFIs) engaged in credit intermediation activities.

<sup>8</sup>Only less than 3% of shadow banks changed their specializations in our sample. Including or excluding these banks barely change the estimation results.

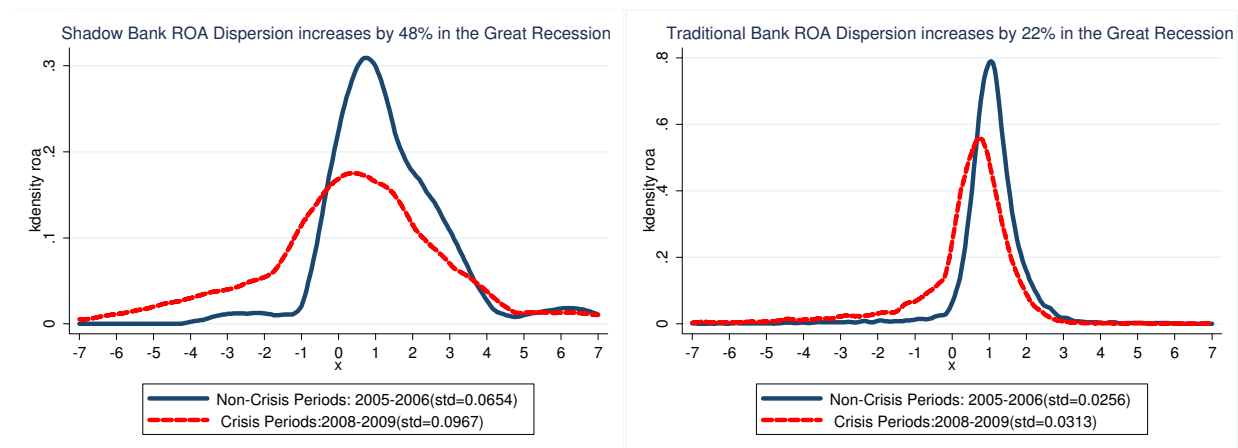
<sup>9</sup>U.S. Flow of Funds only provides aggregated data of different categories of financial institutions. As shown below, one of the disadvantages of aggregate data is that the pattern of the data might be driven by banks in certain asset quantiles in

## 1.2 Stylized Facts

**Stylized Fact 1:** The Shadow banking sector asset return uncertainty increased in the 2007-2009 recession.

The left panel of Figure 1 illustrates the kernel density of return on asset (ROA)<sup>10</sup> for shadow banks during non-crisis periods and crisis periods.<sup>11</sup> The standard deviation of shadow banks' ROA increases by 48% during the crisis. To have a clearer idea about the magnitude of the change, I also show the change of traditional banks's ROA standard deviation for reference. By comparison, the ROA standard deviation of traditional banks increases by only 22% , less than one-half of that of shadow banks. Explaining the difference between shadow banks and commercial banks is beyond the scope of this paper. All the empirical analyses for traditional banks are only shown for comparison and to provide a better understanding of shadow banks.

Figure 1: ROA Dispersion of Banks



Notes: Shadow banks are defined as real estate and mortgage banks, investment banks, micro-financing institutions, securities firms, private banking and asset management companies, investment and trust corporations, finance companies, and group finance companies. Traditional banks are defined as commercial banks, savings banks, cooperative banks and bank holding companies. The whole sample contains 281 shadow banks and 9554 traditional banks for the 1998 to 2013 period, covering 49 states in the U.S.. ROA is the bank's return on assets and is defined as net income divided by total assets. Interest expense is added back into net income when performing this calculation. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009. According to the NBER, the recession began in 12/2007, so 2007 is not a clean "before" or "during" recession year.

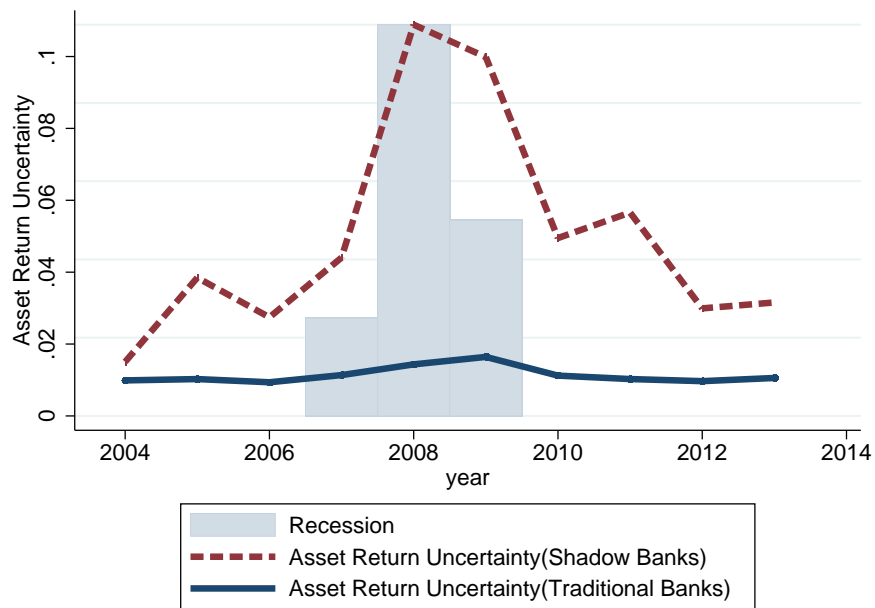
the sample. From a regulatory point of view, the policy prescription will differ if aggregate leverage is driven by large banks rather than a large number of small or mid-size banks.

<sup>10</sup>ROA is bank's return on assets. ROA is often defined as net income divided by total asset. I add interest expense back into net income when performing this calculation.

<sup>11</sup>Following Bloom et al. (2012), non-crisis periods are defined as from the 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009. According to the NBER, the recession began in 12/2007, so 2007 is not a clean "before" or "during" recession year.



Figure 2: Bank Return on Asset Uncertainty



Notes: Return on asset uncertainty is defined as the standard deviation of the residual term after fitting the panel data of individual bank gross ROA into an AR(1) process, controlling for time and bank level fixed effects and other bank level heterogeneities. The classification of shadow banks and traditional banks is shown in the appendix. The grey bar is the NBER recession. Since we only have yearly data, the recession periods are plotted such that the length of grey bar represent how much fraction of any particular year is defined as recession period according to NBER. One quarter of 2007 is in recession, while all of 2008 and two quarters of 2009 are in recession.

To measure the uncertainty of banks' ROA, I follow a standard approach as Foster, Haltiwanger, and Krizan (2001). I assume the bank gross return on asset follows an AR(1) process. To ease notation, I define the bank gross asset return rate  $groa_{it} = 1 + ROA_{it}$ . Then I fit the data  $\{\log(groa_{it})\}_{i=1,\dots,N,t=2004,\dots,2013}$ <sup>12</sup> into an AR(1) process, controlling for time and bank-level fixed effects:

$$\log(groa_{it}) = \rho \log(groa_{it-1}) + \lambda_t + \mu_i + X_{it} + \epsilon_{it}, \quad (1)$$

where  $\lambda_t$  is the year fixed effect (controlling for cyclical shocks),  $\mu_i$  is bank-level fixed effect (controlling for bank-level differences).  $X_{it}$  are other control variables including bank size, asset riskiness, etc. The uncertainty on bank asset return  $\sigma_t$  is then defined as the cross-sectional dispersion of the residual  $\epsilon_{it}$ . The evolution of  $\sigma_t$  is then shown in the Figure 2. The figure shows that the shadow bank return uncertainty increases from 0.044 to 0.109 during the 2007-2009 recessions. The percentage change is 147%, much higher than that of the traditional bank asset return uncertainty, which is only 56%<sup>13</sup>.

**Stylized Fact 2:** Interbank market spreads spiked up during the 2007-2009 financial crisis.

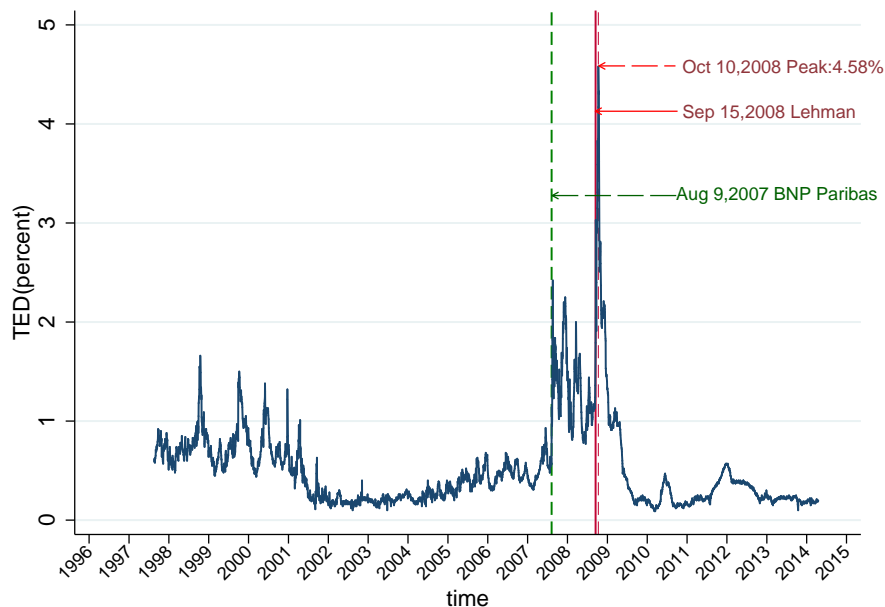
I use the TED spread as the indicator of the interbank market spread. The TED spread is the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"). It is a commonly used indicator of perceived credit risk in the economy. An increase in the TED spread is a sign that lenders believe the risk of default on interbank loans (also known as counterparty risk) is increasing and thus they charge a higher interest rate when lending in the interbank market. I obtain the daily TED spread data from the FRED database and plot it in Figure 3. The average TED spread was approximately 0.6% from the fourth quarter of 2001 until August of 2007 when BNP Paribas's suspended the valuation of three of its hedge funds related to the U.S. asset-backed securities. The market uncertainty increased dramatically and the average interbank credit spread increased sharply to 2.5%. The TED spread continued to increase following Lehman

<sup>12</sup>N is the number of banks in our dataset.

<sup>13</sup>One explanation for this is illustrated in Stylized Fact 4: traditional banks and shadow banks has very different asset composition and funding structure. The exposure to risky asset is much higher for shadow banks. And therefore their asset return uncertainty is much more volatile compared with traditional banks. The measures of asset return uncertainty are robust after controlling for more bank level or industry level heterogeneities, and across different subsamples divided by bank sizes or specializations.

Brothers' bankruptcy on September 15, 2008 and reached its peak of 4.58% on October 10, 2008, 25 days after the bankruptcy of Lehman.

Figure 3: TED Spread



Notes: This figure depicts the change of interbank market spread based on daily TED spread data obtained from the FRED Database. TED spread is the difference between the interest rates on interbank loans and on short-term U.S. government debt (“T-bills”). It is a commonly used indicator of perceived credit risk in the economy.

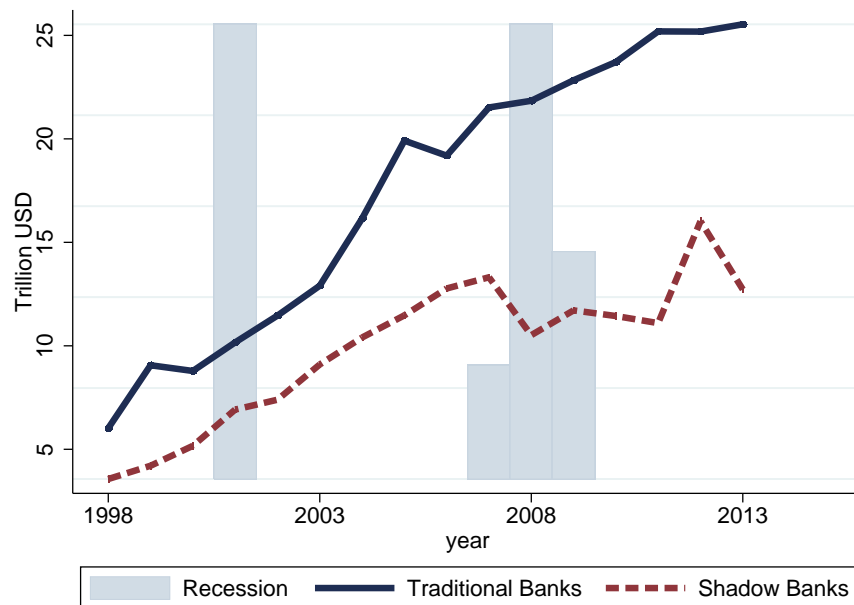
**Stylized Fact 3:** The shadow banking sector asset size shrank by 21% during the 2007-2009 financial crisis.

I obtain the bank-level data from the BankScope database and WorldScope database and calculate the total assets for the U.S. shadow banking sector. The dashed line in Figure 4 depicts the total asset of shadow banks.<sup>14</sup> The units of the Y-axis are trillions of 2005 US dollars. Figure 4 shows that the shadow banking sector has a positive trend in assets. During the 2007-2009 recession, the shadow banking sector asset size shrank by 21%. By comparison, traditional banking sector asset size increased during 2007-2009 crisis, although with a lower growth rate.

Since assets and liabilities of different financial institutions are not netted out during the aggregation. Simply adding up the assets and liabilities of different banks might lead to double counting of

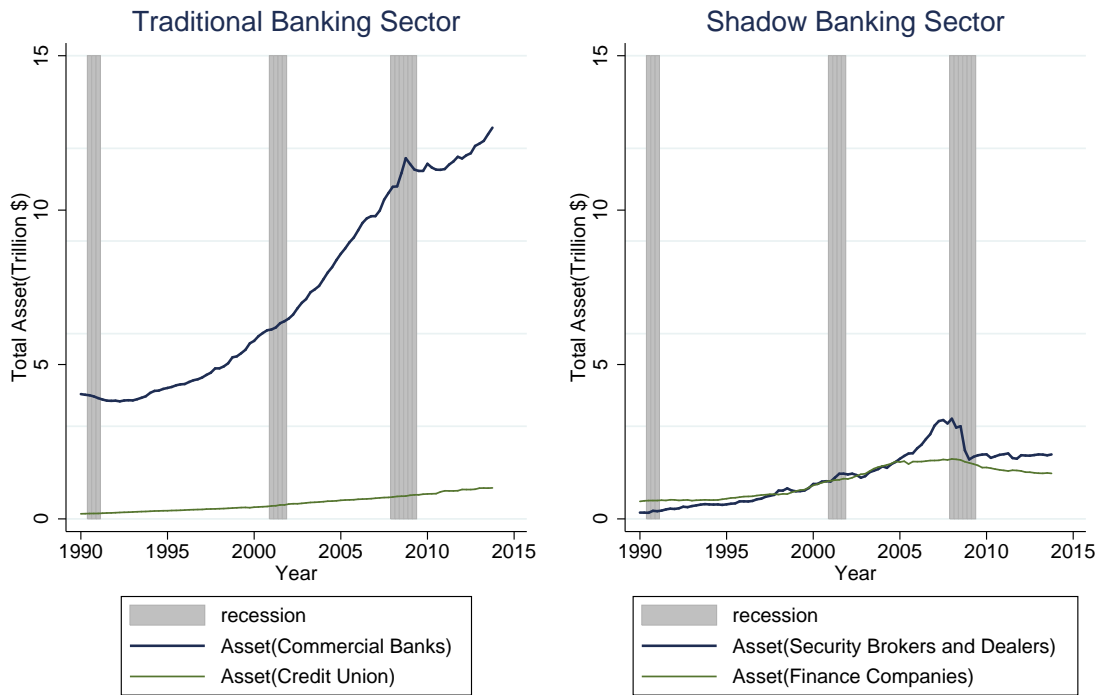
<sup>14</sup>Traditional Banks also engage in shadow banking activities. They set up conduits and the activity of these conduit are not recorded on their balance sheet. In the empirical analysis of this paper, I only focus on the shadow banking activities observable in the data. My estimation of shadow bank size is close to FSB’s estimation using aggregate data.

Figure 4: Total Asset of Banks (BankScope and WorldScope Micro-level Data)



Notes: This figure depicts the change in total asset size of the U.S. traditional and shadow banking sector respectively using bank-level dataset from BankScope and WorldScope database. The classification of shadow banks and traditional banks is shown in the appendix. The grey bar is the NBER recession. Since we only have yearly data, the recession periods are plotted such that the length of grey bar represent how much fraction of any particular year is defined as recession period according to NBER.

Figure 5: Total Asset (US Flow of Fund Aggregate Data)



Notes: This figure depicts the change in total asset size of the U.S. traditional and shadow banking sector respectively using the U.S Flow of Funds quarterly aggregate data. Here I take commercial banks and credit unions as the representative of traditional banks, security brokers, dealers , and finance companies as representative of shadow banks. The grey area are quarters in recession.

asset cross positions. To mitigate this concern, I further check the aggregate asset data from the US Flow of Funds. I take commercial banks and credit unions as the representative of traditional banks, security brokers and dealers, and finance companies as representative of shadow banks. The results are shown in Figure 5. The shaded area is the NBER recession. The units of the Y-axis are Trillions of 2005 US dollars. Similar to Figure 4, shadow banks are much negatively affected: Security brokers and dealers' asset size alone shrank by over 2 trillions, larger than total shrinkage of commercial banks and credit unions combined. From Figure 4 and Figure 5, we can reach the conclusion that the assets of the shadow banking sector shrank during the 2007-2009 recession and the total banking credit shrinkage mainly comes from the contraction of the shadow banking sector.

**Stylized Fact 4:** The leverage of shadow banks decreased during the 2007-2009 financial crisis. The extensive margin contributed more than the intensive margin to the aggregate leverage change of shadow banks. Bigger banks tend to have higher leverage.

I calculate the aggregate leverage for shadow banks and traditional banks in non-crisis periods and crisis periods, respectively. The leverage is defined as total liabilities divided by total assets. The results are shown in Table 1. The leverage of shadow banks decreased by 0.074. Traditional bank leverage decreased by merely 0.005. To get a clearer idea about the contributing factors of the aggregate leverage change, I decompose aggregated leverage change into the intensive margin and extensive margin. I divide the bank asset size into 10 asset quantiles. At each asset quantile  $i$ , banks have a mean asset size  $k_i$ . Denote  $b_{it}$  as the mean debt held by banks at asset quantile  $i$  at period  $t$ , and  $\omega_{it}$  as the measure of banks within asset quantile  $i$  at period  $t$ .  $B_t$  and  $K_t$  are aggregated liabilities and assets, respectively. Then the change in aggregate leverage  $\Delta L_t \equiv \Delta \frac{B_t}{K_t} = \frac{B_t}{K_t} - \frac{B_{t-1}}{K_{t-1}} = \frac{\sum \omega_{it} b_{it}}{\sum \omega_{it} k_i} - \frac{\sum \omega_{it-1} b_{it-1}}{\sum \omega_{it-1} k_i}$ . I denote the total assets of banks within asset quantile  $i$  as a fraction of aggregated assets as  $\alpha_{it} \equiv \frac{\omega_{it} k_i}{\sum \omega_{it} k_i} = \frac{\omega_{it} k_i}{K_{it}}$ , and the leverage of banks at asset quantile  $i$  at time  $t$  as  $l_{it} \equiv \frac{b_{it}}{k_i}$ . Then  $\Delta L_t = \sum \alpha_{it} l_{it} - \sum \alpha_{it-1} l_{it-1} = \sum (l_{it} - l_{it-1}) \alpha_{it-1} + \sum (\alpha_{it} - \alpha_{it-1}) l_{it}$ . The first term of the equation captures the intensive margin leverage change: the change in aggregate leverage resulting from bank of all asset quantiles take a lower leverage, given a fixed asset distribution. The second term captures the extensive margin: the change of aggregate leverage resulting from the change of bank's asset distribution. The contribution of each margin is reported in Table 1. The extensive and intensive margins contribute to 61% and 39% of the aggregate leverage change of shadow banks respectively.

By comparison, the change of aggregate leverage change of traditional banks almost exclusively comes from the intensive margin.

Figure 6 illustrates the leverage for different asset quantiles of banks using the bank-level dataset. Shadow banks of different asset sizes on average choose a lower leverage during the crisis. This captures the intensive margin. Figure 6 also shows that bigger banks tend to have higher leverage; this positive correlation is robust for both type of banks. This result is consistent with Adrian and Shin (2010). As Adrian and Shin (2010) argued, if banks target a leverage ratio, the optimal leverage will not increase with asset values. But if banks target a level of risk exposure, leverage will be positively correlated with assets values. My finding supports the conjecture that banks target a certain level of risk exposure.

Figure 7 depicts the change of bank asset distribution. Shadow banks choose smaller asset size and the whole asset distribution becomes more skewed toward the lower asset level region. This captures the extensive margin in the sense that banks jump across their asset quantile bins<sup>15</sup>.

Table 1: Leverage Change Decomposition

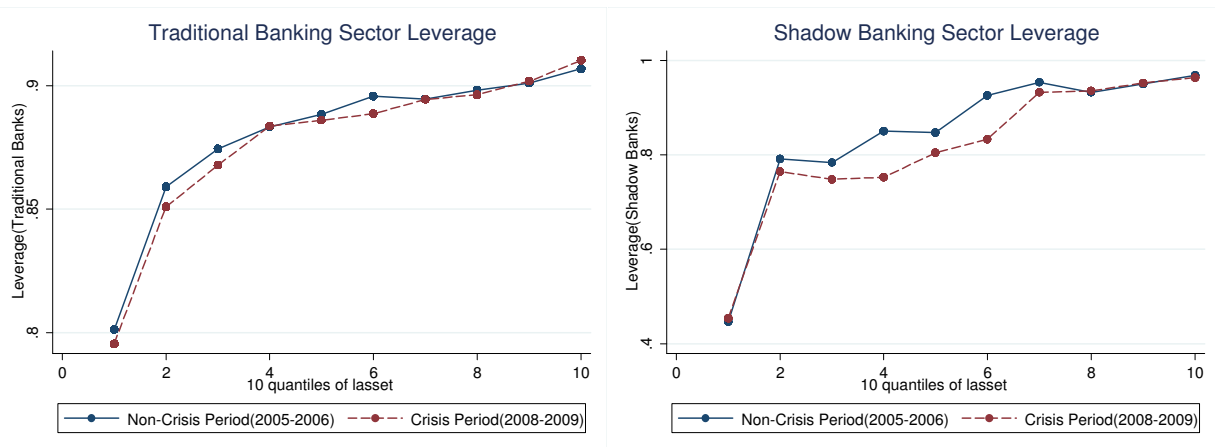
Shadow Banks	non-crisis periods	crisis periods	leverage change
Average leverage	0.969	0.895	-0.074
Extensive margin		61%	
Intensive margin		39%	
Traditional Banks	non-crisis periods	crisis periods	leverage change
Average leverage	0.896	0.891	-0.005
Extensive margin		7%	
Intensive margin		93%	

Notes: The extensive margin is defined as the change in aggregate leverage resulting from change in bank's asset distribution. The intensive margin is defined as the change in aggregate leverage resulting from banks across all asset quantiles choose a different leverage ratio, given a fixed asset distribution. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009.

To further analyze the relationship between asset return uncertainty and bank leverage, I also report the regression of leverage on the uncertainty of the bank asset return, controlling for bank asset size, profitability (gross asset return rate), and risky asset exposure (i.e., fraction of derivative and other securities in total assets) for both types of banks in Tables 2 and 3. To mitigate the concern about reverse causality, I lag all explanatory variables by one year. In 2004, the Securities and Exchange

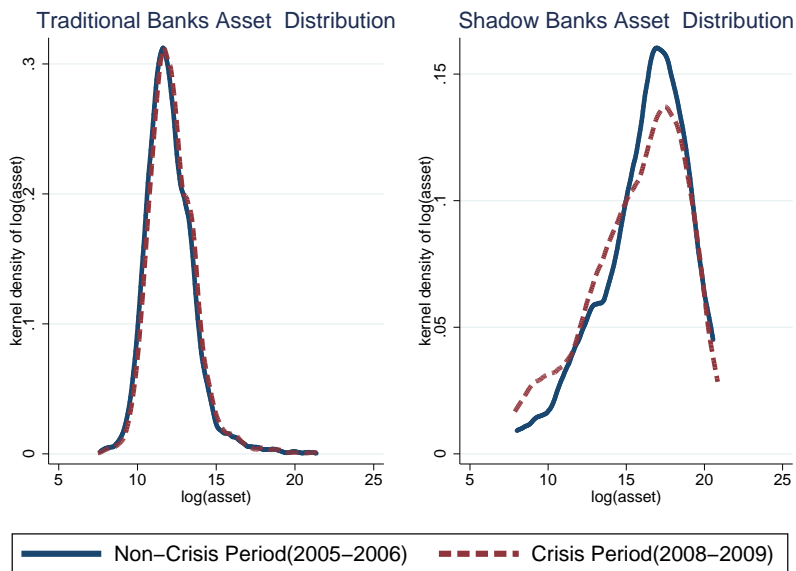
<sup>15</sup>There is actually another extensive margin of deleveraging resulting from the banks which exit the market. Yet I find that this margin's contribution is too small to be relevant for the fluctuation in aggregate leverage. The major contraction of credit intermediation results from the fact that banks remaining on the market provided less credit, not the fact that a few banks such as Lehman Brothers declared bankruptcy.

Figure 6: Leverage over Asset Quantiles



Notes: This figure depicts the change in leverage ratio of shadow banks and traditional banks over ten asset quantiles. Leverage ratio is defined as total debt to total asset ratio within each asset quantile. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009.

Figure 7: Asset Distribution



Notes: This figure depicts the change in asset distribution of shadow banks and traditional banks. The measure of small and medium size shadow banks increases during the recession whereas the distribution of traditional banks barely changes. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009.



Commission (SEC) deregulated the minimum capital requirement for investment banks, freeing leverage ratios from direct regulatory constraint. I therefore include an interaction term between the explanatory variable and an indicator variable that takes the value of one for the observations after 2004 to see whether the leverage choices of shadow banks after 2004 is significantly different from those in earlier years. The first four regressions control for both bank-level fixed effects and time fixed effects, while regression 5 to 8 include asset uncertainty. Since the measure of asset uncertainty only has time-variation and no cross-sectional variation, I drop the time fixed effect in these regressions to avoid multicollinearity. The regression results show that asset size always has a positive impact on the leverage choices of shadow banks. One explanation for this is equity issuance is much more costly than debt issuance. As documented in [Adrian and Shin \(2010\)](#), equity issuance is very sticky. Banks expand their assets mainly through debt issuance. Hence asset size and leverage generically change simultaneously in the same direction. The second takeaway from the regression is that the uncertainty of bank asset return has a negative impact on leverage after 2004. As shown in regressions 6 and 8, the coefficients on asset return uncertainty are both significantly negative for both types of banks. I also find that the profitability of banks has a significantly negative impact on a bank's leverage. This is consistent with the findings of [Kalemli-Ozcan, Sorensen, and Yesiltas \(2011\)](#). As profitability is a source of internal financing, higher profitability means a lower need for external debt financing. I also include the interaction term between uncertainty and asset level to check whether the impact of uncertainty on leverage is different over banks of different asset sizes. Since the coefficients of the interaction term are insignificant. For brevity, I do not report them here.

**Stylized Fact 5:** Shadow banks are very different in terms of both funding structure and exposure to risky assets compared with traditional banks. Shadow banks heavily depend on short-term funding, while traditional banks mainly depend on customer deposits. Shadow banks typically invest more than 60% of their assets on risky financial products, whereas traditional banks invest less than 30% of their assets on such products on average.

Figure 8 illustrates the funding structures of shadow banks and traditional banks. The unit is 2005 trillion USD. Traditional banks highly depend on customer deposits which account for over 60% of traditional banks liability for almost all years in the sample. By comparison, shadow banks highly depend on funds provided by the short-term collateralized debt market. Before 2008, short-term

Table 2: Regression: Leverage Decision of Shadow Banks

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$leverage_{it}$	$leverage_{it}$	$leverage_{it}$	$leverage_{it}$	$leverage_{it}$	$leverage_{it}$	$leverage_{it}$	$leverage_{it}$
$log(asset_{it-1})$	0.0450*** (0.0037)	0.0511*** (0.0038)	0.0288*** (0.0055)	0.0376*** (0.0054)	0.0236*** (0.0046)	0.0312*** (0.0053)	0.0174*** (0.0043)	0.0266*** (0.0051)
$log(asset_{it-1}) * I_{(year>2004)}$		-0.0099*** (0.0016)		-0.0129*** (0.0019)		-0.0044*** (0.0011)		-0.0039*** (0.0011)
$log(gross\ asset\ return_{it-1})$			-0.1173*** (0.0294)	0.0045 (0.0460)	-0.1081*** (0.0292)	0.0478 (0.0471)	-0.0993*** (0.0276)	0.0245 (0.0430)
$log(gross\ asset\ return_{it-1}) * I_{(year>2004)}$				-0.2281*** (0.0595)		-0.2780*** (0.0604)		-0.2430*** (0.0589)
$log(asset\ return\ uncertainty_{t-1})$					-0.0021 (0.0035)	0.0053 (0.0040)	0.0004 (0.0032)	0.0056 (0.0038)
$log(asset\ return\ uncertainty_{t-1}) * I_{(year>2004)}$						-0.0230*** (0.0061)		-0.0174*** (0.0058)
$log(asset\ riskiness_{t-1})$							0.0005 (0.0029)	0.0036 (0.0039)
$log(asset\ riskiness_{t-1}) * I_{(year>2004)}$								-0.0034 (0.0038)
Constant	0.0897 (0.0607)	0.1531** (0.0608)	0.3480*** (0.0879)	0.4169*** (0.0865)	0.4366*** (0.0727)	0.3391*** (0.0817)	0.5442*** (0.0691)	0.4223*** (0.0789)
Bank Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1916	1916	1306	1306	1259	1259	1172	1172
$R^2$	0.1132	0.1146	0.1521	0.0988	0.1247	0.2621	0.2261	0.2744
Number of id	281	281	215	215	214	214	202	202

Notes: Robust asymptotic standard errors reported in parentheses are double-clustered in the bank and time dimension, according to Cameron, Gelbach, and Miller (2011). Shadow banks are defined as all the U.S. real estate and mortgage banks, investment banks, micro-financing institutions, securities firms, private banking and asset management companies, investment and trust corporations, finance companies, and group finance companies in the BankScope and WorldScope database. The sample period is from 1998 to 2013 at annual frequency. The dependent variable is the leverage ratio, which is defined as the total debt over asset ratio of each individual bank. The explanatory variables are the one-period lagged bank asset size, profitability (gross asset return rate), and risky asset exposure (the fraction of derivative and other securities in total asset). \* \* \*  $p < 0.01$ , \*  $p < 0.05$ , \*  $p < 0.1$ .

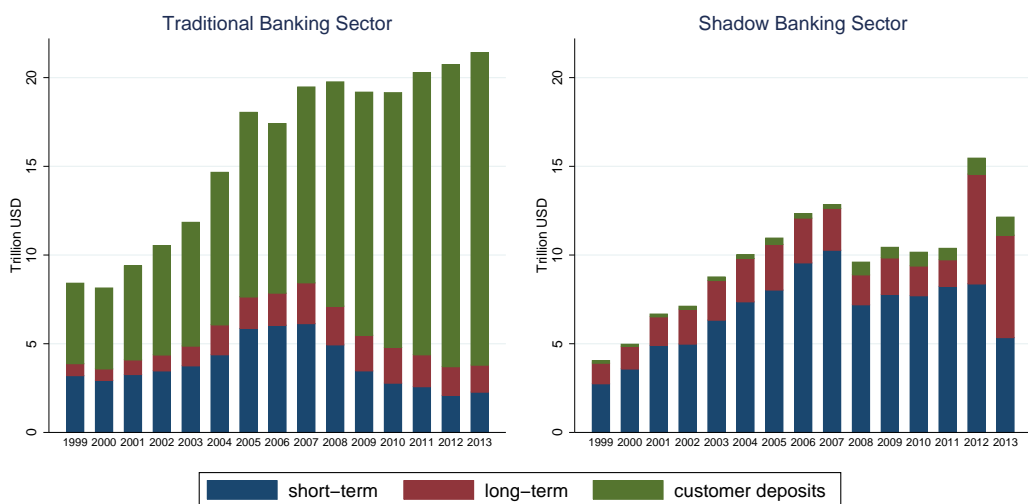
Table 3: Regression: Leverage Decision of Traditional Banks

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>leverage<sub>it</sub></i>	<i>leverage<sub>it</sub></i>	<i>leverage<sub>it</sub></i>	<i>leverage<sub>it</sub></i>	<i>leverage<sub>it</sub></i>	<i>leverage<sub>it</sub></i>	<i>leverage<sub>it</sub></i>	<i>leverage<sub>it</sub></i>
$\log(asset_{it-1})$	0.0248*** (0.0003)	0.0275*** (0.0003)	0.0251*** (0.0003)	0.0278*** (0.0003)	0.0140*** (0.0002)	0.0233*** (0.0003)	0.0111*** (0.0002)	0.0203*** (0.0003)
$\log(asset_{it-1}) * 1_{(year>2004)}$		-0.0033*** (0.0001)		-0.0033*** (0.0001)		-0.0017*** (0.0001)		-0.0016*** (0.0001)
$\log(gross\ asset\ return_{it-1})$			-0.0377*** (0.0055)	0.0200*** (0.0069)	-0.0064 (0.0055)	0.0303*** (0.0069)	-0.0213*** (0.0054)	-0.0133* (0.0069)
$\log(gross\ asset\ return_{it-1}) * 1_{(year>2004)}$				-0.1551*** (0.0089)		-0.1560*** (0.0089)		-0.0973*** (0.0092)
$\log(asset\ return\ uncertainty_{t-1})$					-0.0013*** (0.0003)	-0.0021*** (0.0003)	-0.0011*** (0.0003)	-0.0019*** (0.0003)
$\log(asset\ return\ uncertainty_{t-1}) * 1_{(year>2004)}$						-0.0021*** (0.0003)		-0.00302*** (0.0003)
$\log(asset\ riskiness_{it-1})$							-0.0012*** (0.0002)	-0.0042*** (0.0002)
$\log(asset\ riskiness_{it-1}) * 1_{(year>2004)}$								0.0028*** (0.0002)
Constant	0.6159*** (0.0036)	0.5807*** (0.0039)	0.6132*** (0.0037)	0.5765*** (0.0039)	0.7101*** (0.0033)	0.6010*** (0.0039)	0.7452*** (0.0032)	0.6331*** (0.0039)
Bank Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110656	110656	110652	110652	110141	110141	108208	108208
R <sup>2</sup>	0.0705	0.0760	0.0710	0.0795	0.0366	0.0648	0.0264	0.0529
Number of id	9498	9498	9497	9497	9497	9497	9456	9456

Notes: Robust asymptotic standard errors reported in parentheses are double-clustered in the bank and time dimension, according to Cameron et al. (2011). Traditional banks are defined as all the U.S. commercial banks, savings banks, cooperative banks and bank holding companies in BankScope and WorldScope databases. The sample period is from 1998 to 2013 at annual frequency. The dependent variable is leverage ratio which is defined as the total debt over asset ratio of each individual bank. The explanatory variables are the one-period lagged bank asset size, profitability (gross asset return rate) and risky asset exposure (the fraction of derivative and other securities in total asset). \* \* \*  $p < 0.01$ , \* \*  $p < 0.05$ , \*  $p < 0.1$ .

funding accounts for over 70% of the funding for shadow banks. And since 2007, the funding provided by the short-term collateralized market has declined, and shadow banks gradually switched to rely more on long-term funding after 2011. Customer deposit has always been an almost negligible funding source of shadow banks. Its proportion in shadow banks' total funding is less than 10% for every year of the sample. Given this feature, when modeling the liability side of shadow banks, I abstract from the customer deposits.

Figure 8: Funding Structure



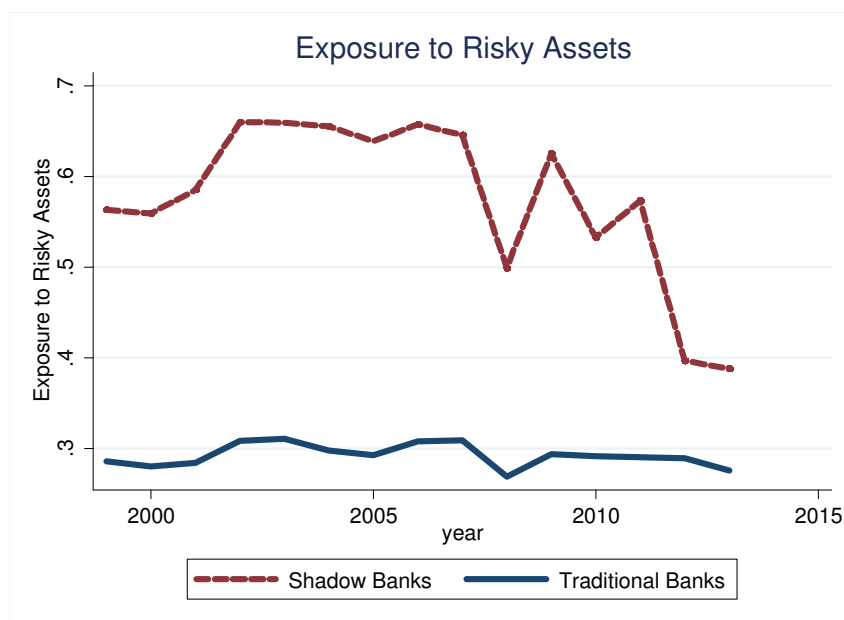
Notes: This figure depicts the change of funding structure of shadow banks and traditional banks. Short-term and long-term refers to the short-term debt and long-term debt the banks hold respectively. The classification of shadow banks and traditional banks is shown in the Appendix.

Figure 9 illustrates that shadow banks invest over 60% of their assets in risky assets (derivative and other securities), while traditional banks invest less than 30% of their assets in these risky products.

In sum, based on the first four stylized facts, I find that: shadow bank asset return uncertainty increases during the 2007-2009 crisis; interbank spread also increases, forcing shadow banks to deleverage and reduce their asset sizes. Since shadow banks contribute more to the total banking credit contraction in the recent crisis compared with traditional banks, in this paper, I focus on the shadow banks<sup>16</sup>. To explain these empirical findings, I build a model that provides a micro-foundation for the impact of uncertainty on the financing and leverage decisions of shadow banks. And because shadow banks have very different asset and liability composition compared with traditional banks as

<sup>16</sup>Building a unified model including the both types of banks and explaining the difference between them is clearly desirable. I leave this for future research. Given the limited role traditional banks played in the recent recession, to keep the model as simple as possible, I focus on shadow banks in this paper.

Figure 9: Risk Exposure



Notes: This figure depicts the change in the asset risk exposure of shadow banks and traditional banks. Risk exposure is defined as the fraction of total asset invested in derivative and other securities. The classification of shadow banks and traditional banks is shown in the Appendix.

illustrated in Stylized Fact 5, different from conventional modelling about traditional banks, I abstract from customer deposits and assume shadow banks totally depends on short-term funding when I model the shadow banks <sup>17</sup>.

## 2 A Simple Two-Period Model

In this section, I develop a simple two-period model to illustrate the key mechanism of the paper. Assume there is a representative shadow bank which finances its investment in risky loans using risky debt and equity. In the first period, the bank issues equity and debt and invests in a risky project. The bank's balance sheet can be written as :  $qb + n/\chi = k$ , where  $\chi$  is the floatation cost of issuing equity,  $\chi > 1$ ,  $q$  is the price of risky bond the bank issues, and  $n$  is the amount of equity issuance. <sup>18</sup>

<sup>17</sup>As illustrated in Section 4, the funding structure and asset composition of shadow banks makes the bank's problem inherently similar to that of a firm with constant return to scale production technology. The other difference is that banks use short-term debt to fund long-term projects, whereas firms usually fund long-term project with long-term debt. Thus, the degree of maturity mismatch between the bank's assets and liabilities is much higher than that of a generic firm.

<sup>18</sup>Floatation cost is incurred by a publicly traded company when it issues new securities. It includes expenses such as underwriting fees, legal fees, and registration fees.

In the second period , the bank needs to repay  $b$ . Assume the total loan return is  $zk$ , where  $z$  captures the gross loan return rate,  $\log z \sim N(-\frac{\sigma^2}{2}, \sigma^2)$ .

When  $zk < b$ , the bank cannot repay its debt . Since the value of repaying is negative, smaller than the value of default, which is zero in this case, the bank would choose to default. Thus we get the default cutoff of the asset return rate  $z^* = \frac{b}{k}$ . Note that  $z^*$  also denotes the leverage ratio. When bank defaults, for simplicity, I assume the lender gets  $\theta$  fraction of total loan return  $zk$  as recovery.  $\theta < 1$ ,  $1 - \theta$  captures the bankruptcy costs.

Then the bank's discounted expected net worth in the second period is :  $\beta \int_{z^*}^1 [zk - b] dF(z)$ , where  $\beta$  is the discount factor, and  $F(z)$  is the cumulative distribution function of gross loan return rate  $z$ . Denote  $\Psi(k, 0)$  as the quadratic adjustment cost of investment<sup>19</sup>. The bank's net payoff maximization problem can be written as:

$$\max_{b,k} -n - \Psi(k, 0) + \beta \int_{z^*}^1 [zk - b] dF(z) \quad (2)$$

$$s.t \ n = (k - qb)\chi \quad (3)$$

$$z^* = \frac{b}{k} \quad (4)$$

$$qb = \frac{1}{1+r} \left[ \int_{z^*} b dF(z) + \int_0^{z^*} (\theta zk) dF(z) \right], \quad (5)$$

Substitute  $b$  with  $k$  and  $z^*$ , the bank's problem is equivalent to:

$$\max_{k,z^*} \left\{ -k + \frac{1}{1+r} \left[ z^*(1 - F(z^*))k + \int_0^{z^*} \theta zk dF(z) \right] \right\} \chi - \Psi(k, 0) + \beta \int_{z^*}^{\infty} [k(z - z^*)] dF(z). \quad (6)$$

F.O.C:

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<sup>19</sup>We need a quadratic adjustment cost on loan investment or decreasing return to loan to avoid corner solutions for the bank's problem. Without a quadratic adjustment cost, maximizing linear function of  $k$  subject to a budget set linear in  $k$  would lead to corner solutions.

with respect to  $k$ :

$$1 + \Psi'(k, 0) = \frac{\chi}{1+r} \left[ \int_0^{z^*} z\theta dF(z) + z^*(1 - F(z^*)) \right] + \beta \int_{z^*}^{\infty} (z - z^*)dF(z). \quad (7)$$

The left-hand side is the marginal cost of a loan, whereas the right-hand side is the marginal return of loan  $k$ .

with respect to  $z^*$ :

$$\frac{\chi}{1+r}(1 - \theta)z^*f(z^*) = \left(\frac{\chi}{1+r} - \beta\right)(1 - F(z^*)). \quad (8)$$

$f(z)$  is the probability distribution function of gross loan return rate  $z$ . The left-hand side is the marginal cost of leverage (the increase of expected bankruptcy cost). The right-hand side is the marginal benefit of leverage (lower flotation cost in non-default states ).

From equation (8), we can get:

$$z^* = \frac{1}{1-\theta} \left[ 1 - \frac{\beta(1+r)}{\chi} \right] \left[ \frac{f(z^*)}{1-F(z^*)} \right]^{-1} \quad (9)$$

Denote  $\pi(z^*) = \frac{f(z^*)}{1-F(z^*)}$ . This is the hazard rate<sup>20</sup>. As shown in the Appendix, for a wide range of value of  $\sigma$  and  $z^*$ , the hazard rate is an increasing function of the standard deviation of the underlying asset return distribution. We have the following four propositions.

**Proposition 1:** Bank's leverage  $z^*$  decreases in its discount factor  $\beta$  and increases in flotation cost  $\chi$ . When the bank is sufficiently patient,  $\beta = \frac{\chi}{1+r}$ , it totally depends on internal(equity) finance (i.e.,  $z^* = 0$ ).

Proof: See Appendix.

**Proposition 2:** When the bank is sufficiently impatient,  $\beta < \frac{\chi}{1+r}$ , as long as the hazard rate is an increasing function of asset return uncertainty, i.e.,  $\frac{\partial \pi(z^*)}{\partial \sigma} > 0$ , bank leverage is a decreasing function of the asset return uncertainty,  $\frac{\partial z^*}{\partial \sigma} < 0$

Proof: See Appendix.

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<sup>20</sup>Intuitively, hazard rate is the probability of get the worst draw  $z^*$  conditional on  $z$  is higher or equal to  $z^*$ .

**Proposition 3:** Bank asset size is a decreasing function of the asset return uncertainty:  $\frac{\partial k}{\partial \sigma} < 0$ .

Proof: See Appendix.

**Proposition 4:** The increase in asset return uncertainty increases the interest spread the bank faces when it issues debt.

Proof: See Appendix.

I prove in the appendix that when the hazard rate is an increasing function of the standard deviation of the asset return distribution, leverage increases when volatility increases. The intuition for this is when volatility increases, the default risk increases and interest spread increases. Facing a higher financing cost, the bank has the incentive to lower default risk by reducing its leverage. I also show in the Appendix that the negative effect of a decrease in leverage on default risk typically cannot offset the direct impact of volatility on default risk. Thus, the net effect is that the default risk increases and the bank still faces a higher spread when it issues debt.

### 3 Full Model

In this section, I extend the model to an infinite horizon. I assume there is a continuum of banks borrowing from the interbank market using risky debt. A clearing house take funds from some banks and lends to other banks. In each period, depending on the idiosyncratic shock to its asset return, a bank would choose to borrow from the clearing house or save in the clearing house. For simplicity, assume that when a bank chooses to save in the clearing house ( $b < 0$ ), it only receives risk-free rate  $r$  as the rate of return. Each bank invests in a risky loan. The risky loan gives the bank the gross return  $z_t k_t$ .  $z_t$  is the idiosyncratic gross rate of return on the bank's assets<sup>21</sup> which captures the investment quality of the loan. Assume the idiosyncratic asset return shock  $z_t$  follows a Markov process with transition function  $\pi_z(z_t|z_{t-1}, \sigma_{t-1})$ , where  $\sigma_{t-1}$  is an aggregate shock to the standard deviation of idiosyncratic asset return shocks. The aggregate shock  $\sigma_t$  follows a Markov process with transition function  $\pi_\sigma(\sigma_t|\sigma_{t-1})$ .

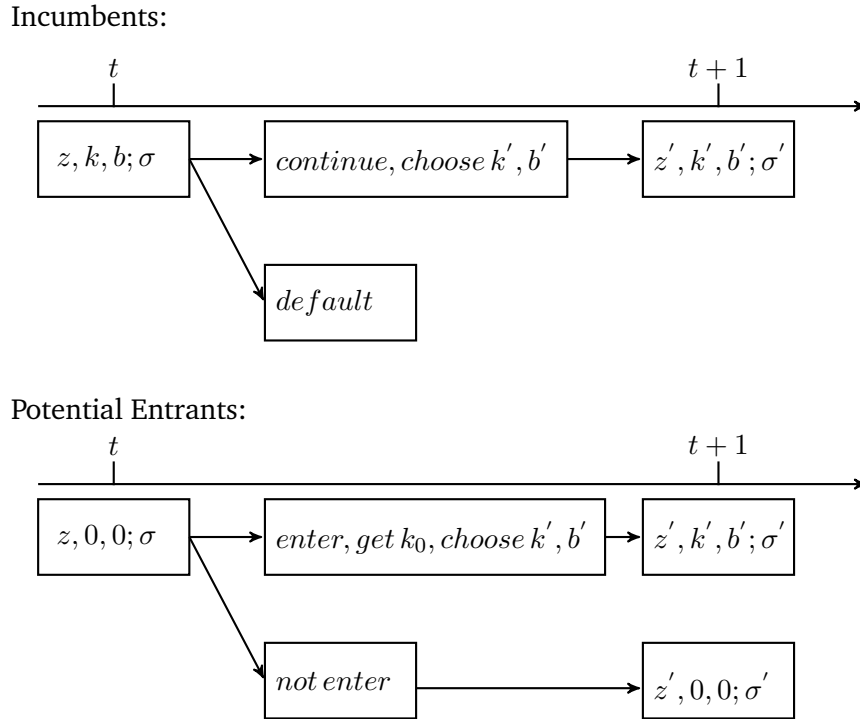
The timing of the model is illustrated in Figure 10. In each period, based on an idiosyncratic state variable vector  $s = \{z, k, b\}$  and aggregate state variable  $S = \sigma$ , the incumbent bank would choose

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<sup>21</sup>The empirical counterpart for  $z_t$  would be bank's ROA+1.



Figure 10: Timeline from Time  $t$  to  $t + 1$



whether to default, as well as how much to borrow from the interbank market- $b'$ , and how much risky loan to initiate- $k'$ .

Different from a conventional one-period loan, the risky loan here is a long-term loan. In each period, only a fraction  $\delta$  of the loan matures. The rest of the loan  $(1 - \delta)k_t$  is rolled over to the next period. The law of motion of the loan is given by:  $k' = (1 - \delta)k + i$ , where  $i$  is the amount of new loans that are invested at current period. As documented by a rich body of literature (see Brunnermeier, Gorton, and Krishnamurthy (2014), Farhi and Tirole (2012), Krishnamurthy (2010), etc), maturity mismatch and associated firesale cost play a very important role in amplifying the contraction of the economy<sup>22</sup>. Thus I include these features<sup>23</sup> in the model. Introducing these features also help us conveniently analyzing the government interventions in the next section. When the government

<sup>22</sup>Firesale costs and maturity mismatch are inherently correlated with each other. Given a fixed investment strategy, the higher is the degree of maturity mismatch, the more likely the bank would be forced to firesale its long-term assets. A direction for future research is to consider the impact of a firesale on the price of assets that are not firesaled. The firesale can result in a decrease in the value of assets that are not sold. This would lead to a vicious cycle and further amplify an economic downturn.

<sup>23</sup>Assets and liabilities exhibit a maturity mismatch, which is a characteristic of the shadow banks. These institutions invest in long-term risky financial assets largely funded by short-term debt that must be rolled over frequently. The model is one of shadow banking instead of commercial banking because there is no government insurance present on any portion of the banks assets, nor is there any funding via deposits.

intervenes, banks can sell a certain fraction of their assets to the government at full value, thus avoiding the cost of firesale.

Table 4: Balance Sheet of Banks

Assets	Liabilities
Long-term asset $(1 - \delta)k_t$	Net worth $n_t$
Cash flow $z_t k_t - (1 - \delta)k_t$	Risky debt $b_t - q_t b_{t+1}$

The balance sheet of an incumbent bank when it needs to repay its debt is shown in Table 4. On the asset side, the total gross asset return consists of two parts: cash flow and long-term assets. In each period, only  $\delta$  fraction of the loan is due. The cash flow of banks can be written as  $z_t k_t - (1 - \delta)k_t$ <sup>24</sup>. I allow the bank to issue new debt to pay old debt. Hence, in each period, the net debt the bank need to repay can be written as  $b_t - q_t b_{t+1}$ . Denote the cash balance to be  $c$ , which is the cash flow minus the amount of debt due plus the new debt issued in each period:  $c \equiv z k - (1 - \delta)k - b + q b'$ . When the cash balance becomes negative, the bank firesales part of its long-term assets. Assume when the bank firesales its long-term assets, it can only get  $\varsigma$  fraction of the total value, where  $0 < \varsigma < 1$ . The net worth of the bank is equal to what is remained in the asset side after paying the debt due:

$$n \equiv \begin{cases} c + (1 - \delta)k & \text{if } c \geq 0 \\ (1 - \delta)k + \frac{c}{\varsigma} & \text{if } c < 0 \end{cases} \quad 25$$

The incumbent bank's problem is as follows. In each period, the bank would choose to default or not to default:

$$V(z, k, b; \sigma) = \max_{d \in \{0,1\}} (1 - d)V^c(z, k, b; \sigma) + dV^d(z; \sigma). \quad (10)$$

The value of continuation is determined by the following Bellman equation:

$$V^c(z, k, b; \sigma) = \max_{\{b', k'\}} \left\{ (1 + \gamma_e 1_{\{e < 0\}} - \tau_d 1_{\{e > 0\}})e + \beta EV(z', k', b'; \sigma') \right\} \quad (11)$$

<sup>24</sup> $z$  is the gross return on bank assets. One way to understand this is to denote  $z = 1 + r_k$ , where  $r_k$  is the asset return rate. Then cash flow would equal to  $(r_k + \delta)k$ , in which  $r_k k$  is the interest payment,  $\delta k$  is the fraction of principal paid in period  $t$ .  $(1 - \delta)$  fraction of principal is left to the next period.

<sup>25</sup>When  $c < 0$ , the bank does not have enough cash flow to repay the debt. It only need to firesale part of its long-term assets. The amount of assets the bank need to firesale equals the debt due  $|c|$  divided by the firesale discount rate  $\varsigma$ .

$$e = \begin{cases} c + (1 - \delta)k - k' - \Phi(k', k) & \text{if } c \geq 0 \\ (1 - \delta)k + \frac{c}{\xi} - k' - \Phi(k', k) & \text{if } c < 0 \end{cases}$$

where  $\Phi(k', k)$  is the quadratic asset adjustment cost:  $\Phi(k', k) = \frac{\phi}{2} \left( \frac{k' - (1 - \delta)k}{k} \right)^2 k$ <sup>26</sup>.  $d$  is the default decision of the bank; when  $d = 1$ , the bank chooses to default.  $e$  is the dividend; when  $e < 0$ , the bank has to pay an extra equity issuance cost of  $\gamma_e$ . When  $e > 0$ , the bank pays a dividend; the dividend tax rate is  $\tau_d$ .

I allow for the presence of both convex and non-convex adjustment costs in asset size. As is well known in the literature, it is the presence of the non-convex adjustment costs that leads to a real options or wait-and-see effect of uncertainty shocks. One concern about the uncertainty literature is that uncertainty might increase the investment level if the bank can adjust the asset size freely to take advantage of a good asset return shock while shrinking size when the asset return is low. The redistribution of assets across efficient and inefficient banks might result in an increase in the total investment level. This is the classical Oi-Hartman-Abel effect. However, this effect depends on whether a bank can adjust its asset size frequently and with very low adjustment cost. As will be shown later, in my model, both the quadratic asset size adjustment cost and firesale cost dampen the Oi-Hartman-Abel effect in the short run.

Assume the value of default is zero:

$$V^d(z; \sigma) = 0. \quad (12)$$

In each period, there are also a continuum of idle bankers deciding whether to start a new bank based on their idiosyncratic shocks and aggregate shocks. I call them potential entrants. A potential entrant would start a new bank if the value of entry  $V^e$  is non-negative. An entrant starts with start-up asset  $k_0$  and decides on the optimal  $k'$  and  $b'$ :

$$V^e(z, \sigma) = \max_{\{b', k'\}} \left\{ (1 + \gamma_e 1_{\{e < 0\}} - \tau_d 1_{\{e > 0\}}) e + \beta EV(z', k', b'; \sigma') \right\} \quad (13)$$

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<sup>26</sup>The microfoundation of asset size adjustment cost is that when a bank adjusts its asset size, it needs to pay a cost to examine the quality of a new loan and pay for the legal fees and possible personnel adjustment costs.

$$e = qb' - k' - \Phi(k', k_0). \quad (14)$$

The price schedule of risky debt offered by a clearing house can be written as:

$$q(z, k', b'; \sigma) = \frac{1 - \iint d(z', k', b'; \sigma') f(z'|z, \sigma') g(\sigma'|\sigma) dz d\sigma}{1 + r} + \frac{\iint d(z', k', b'; \sigma') R(z', k', b') f(z'|z, \sigma') g(\sigma'|\sigma) dz d\sigma}{(1 + r)b'} - \frac{\xi}{b'}, \quad (15)$$

where  $R(z, k, b)$  is the recovery of lender when the bank defaults.  $\xi$  is the fixed credit cost.<sup>27</sup>

$f(z'|z, \sigma')$  is the probability distribution function for the gross asset return rate  $z$  and  $g(\sigma'|\sigma)$  is the probability distribution function for the asset return uncertainty<sup>28</sup>.

$$R(z, k, b) = \max \{0, \min [b, zk - (1 - \varsigma)(1 - \delta)k - \Phi(k, 0)]\}. \quad (16)$$

### Definition 1:

An equilibrium<sup>29</sup> consists of the policy function  $k'(z, k, b; \sigma)$ ,  $b'(z, k, b; \sigma)$ , value function of banks  $V(z, k, b; \sigma)$ ,  $V^c(z, k, b; \sigma)$ ,  $V^d(z, \sigma)$ , value function of new entrants  $V^e(z, \sigma)$ , bond pricing function  $q(z, k, b; \sigma)$ , recovery function  $R(z, k, b)$  such that:

(1) Given the bond pricing function  $q(z, k, b; \sigma)$ , the policy and value function of banks solve their optimization problem;

(2) Given recovery function  $R(z, k, b)$  and bond pricing function  $q(z, k, b; \sigma)$ , lenders in the interbank market break even.

<sup>27</sup>Fixed credit cost is necessary to generate the positive correlation between asset size and leverage in this model environment. It inherently captures the legal fees and account management cost when a bank decides to borrow from the interbank market. Without fixed credit cost, small banks would depend highly on debt finance and this would make the leverage schedule over asset quantiles counterfactually downward sloping.

<sup>28</sup>Here I only consider partial equilibrium. Because there exists aggregate fluctuation, there is no stationary distribution. But if we keep aggregate state variable unchanged for a sufficient long time, we would obtain an ergodic distribution of assets and risky debts.

<sup>29</sup>Detailed appendix containing the proof for the existence and uniqueness of the equilibrium is available upon request.

## 4 Quantitative Analysis

### 4.1 Estimation

There are 14 parameters in this model, as shown in Table 5. Two parameters are calibrated and the rest are jointly estimated using SMM. I assume that the bank asset return has two components: a permanent component  $a$  and an idiosyncratic component  $v$ . In particular,

$$z_{it} = a_i + v_{it}. \quad (17)$$

Following Arellano, Bai, and Zhang (2012b) and Midrigan and Xu (2014), I assume that the permanent component follows a Pareto distribution with an upper bound  $A$  and a shape parameter  $\mu$ , i.e

$$Pr(\exp(a_i) \leq x) = \frac{1 - x^{-\mu}}{1 - A^{-\mu}}. \quad (18)$$

The idiosyncratic component  $v_{it}$  follows an AR(1) process,

$$\log(v_{it}) = \rho_v \log(v_{it-1}) + \lambda_t + \sigma_{t-1} \epsilon_{it} \quad (19)$$

$\epsilon_{it} \sim N(0, 1)$ . I impose  $\lambda_t = -\frac{\sigma_{t-1}^2}{2}$  so as to keep the mean level of  $v_{it}$ .

The discrete process for the aggregate shocks approximates the continuous process:

$$\log(\sigma_t) = (1 - \rho_\sigma) \log \mu_\sigma + \rho_\sigma \log(\sigma_{t-1}) + \nu_t, \quad (20)$$

where  $\nu_t \sim N(0, \varphi^2)$ .

The discrete Markov chain is then discretized into two aggregate shocks<sup>30</sup> and five discrete sets of values for the asset return shock for each of the two aggregate shocks. These approximations follow the methods of Tauchen and Hussey (1991). The permanent productivity is discretized into five levels, which are given by the 5th, 25th, 50th, 75th, and 95th percentile of the Pareto distribution.

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<sup>30</sup>Assume  $\sigma$  can take two values:  $\sigma_l$  and  $\sigma_h$ . The transition matrix of  $\sigma$  is  $\pi = \begin{bmatrix} p_{ll} & p_{lh} \\ p_{hl} & p_{hh} \end{bmatrix}$ .  $z$  and  $\sigma$  are correlated with each other. The transition matrix of  $z$  depends on the realization of  $\sigma'$ .

Table 5: Model Parameters and Target Moments

*A. Parameter Estimates*

Calibrated Parameters	Value	Description
$\beta$	0.96	discount factor
$\tau_d$	0.12	dividend tax
Estimated Parameters	Value	Description
$\gamma_e$	0.0612(0.0121)	equity issuance cost
$\varsigma$	0.6149(0.0527)	firesale cost
$\delta$	0.3274(0.0144)	degree of maturity mismatch
$\xi$	0.0093 (0.0083)	fixed credit cost
$k_0$	0.0080 (0.0014)	entrant start-up asset
$\phi$	1.3336 (0.0320)	asset size adjustment cost
$\rho_v$	0.8042(0.0978)	persistence of asset return
$\rho_\sigma$	0.7687 (0.1547)	asset return uncertainty persistence
$\mu_\sigma$	0.0345 (0.0021)	asset return uncertainty mean
$\varphi$	0.1492 (0.0439)	standard deviation of uncertainty shock
$\mu$	3.3712(0.5741)	Pareto distribution shape
$A$	11.5771(2.1043)	Pareto distribution upper bound

*B. Moments*

Target Moments	Data	Model	<i>t</i> -statistics
mean of leverage	0.9541	0.9489	0.1714
Std of leverage	0.1917	0.0847	1.2516
autocorrelation of leverage	0.8514	0.6874	0.3470
mean of asset growth	0.0447	0.0378	0.4149
Std of asset growth rate	0.0035	0.0142	-0.1477
autocorrelation of asset growth rate	0.8997	0.9409	-0.2158
mean default rate	0.0110	0.0098	1.4121
mean of dividend/asset ratio	0.0214	0.0369	-0.0011
Std of dividend/asset ratio	0.0145	0.0019	1.5620
autocorrelation of dividend/asset ratio	0.7949	0.8532	-0.3314
mean entrant leverage	0.9718	0.9945	-0.6678
mean entrant growth	0.2417	0.1007	1.1788
IQR(75/25) leverage slope	1.1715	1.1954	-0.0143

Notes: Calculations are based on an annual sample of shadow banks from the BankScope and WorldScope databases. The estimation is done with SMM, which chooses model parameters by matching the moments from a simulated panel of banks to the corresponding moments from the data. Panel A reports the estimated parameters, with clustered standard deviation in the parentheses. Panel B reports the simulated and actual moments and the clustered *t*-statistics for the differences between the corresponding moments.

The annual discount factor  $\beta$  is set to 0.96, which is a standard value for annual RBC models. The annual risk-free interest rate  $r$  is 0.03, which is calculated using my sample period of the three-month T-bill rate minus the rate of growth in the Consumer Price Index. Dividend  $\tau_d$  is set to 0.12 following [Hennessy and Whited \(2007\)](#).

The rest of the 12 parameters include the following: the fraction of loan due each period  $\delta$ , equity issuance cost  $\gamma_e$ , firesale cost  $\varsigma$ , parameters governing aggregate shocks  $\rho_\sigma, \mu_\sigma, \varphi$ , the asset adjustment cost  $\phi$ , the persistence of asset return  $\rho_v$ , credit fixed cost  $\xi$ , entrant start-up asset  $k_0$ , and two parameters  $\mu$  and  $A$  which govern the Pareto distribution of the permanent productivity. They are jointly estimated to match the following 13 moments: the mean of default rate, the mean, the standard deviation, and the auto-correlation of leverage, asset growth rate, and dividend to asset ratio of shadow banks, the mean leverage and growth of new entrant banks, and the slope of the leverage schedule using simulated methods of moments (SMM). The detailed estimation procedure is illustrated in the Appendix. I report actual data moments, model moments and  $t$  statistics which test whether data moments and model-generated moments are statistically significantly different. The model tightly matches the 13 data moments. No simulated moment is statistically significantly different from its actual data counterpart.

## 4.2 Identification

The success of SMM estimation depends on model identification, which requires that we choose moments that are sensitive to variations in the structural parameters. I now describe and rationalize the moments that I choose to match. The credit fixed cost  $\xi$ , adjustment cost  $\phi$ , and firesale cost  $\varsigma$  are most relevant for the bank's leverage choice. The fixed credit cost affects both the mean and standard deviation of leverage ratios. A lower  $\xi$  increases mean leverage and decreases the standard deviation of leverage. The estimation requires a positive fixed credit costs for the economy to replicate the observed pattern of leverage distribution of the U.S. shadow banking industry. The asset adjustment cost  $\phi$  is more relevant for the standard deviation and persistence of leverage. The higher the adjustment cost  $\phi$ , the less willing is the bank to change its asset level, hence the standard deviation of leverage would be the smaller, and the autocorrelation of leverage would be higher. The smaller the firesale cost parameter  $\varsigma$ , the larger the loss the bank would suffer during financial distress. Hence,

the bank would take lower leverage. The three parameters  $\rho_\sigma, \mu_\sigma, \varphi$  that govern the persistence, level and volatility of aggregate shock are most closely related to the auto-correlation, mean and standard deviation of asset growth, respectively. They would also indirectly affect the standard deviation of dividend-to-asset ratio by changing the standard deviation of the bank's asset return AR(1) processes.  $k_0$  and  $\gamma_e$  mainly affect the mean leverage and the growth rate of entrants. The measure of entrants in this model is equal to the measure of defaulted banks in the ergodic distribution. Thus  $k_0$  is also indirectly related to mean default probability. The equity issuance cost parameter  $\gamma_e$  directly affects the mean of dividend to asset ratio. The asset return persistence parameter  $\rho_v$  is most closely related to the persistence of the dividend-to-asset ratio. The shape parameters and upper bound of Pareto distribution determine the bank's asset distribution. The smaller the shape parameter, the fatter the right tail of bank distribution<sup>31</sup>, and the higher the concentration of market share. The upper bound of the truncated Pareto distribution determines the degree of permanent technology heterogeneity across banks. The shape and upper bound of the Pareto distribution would thus indirectly affect the all other moments through their impacts on the bank's distribution. They help me to match the slope of the leverage schedule. The higher the upper bound of the Pareto distribution and the smaller the shape parameter, the more heterogeneous the banks will be. Although the leverage schedule slope within each cohort of permanent productivity might only be slightly positive or even negative, with large enough heterogeneity in the permanent productivity, the aggregate leverage schedule can be upward sloping.

## 4.3 Model Implications

### 4.3.1 Policy Rules and Interest Spread Schedule

In Figure 11, I plot the optimal policy rules for the asset size. The model generates a positive correlation between the current asset size and the future asset size. Banks that have higher asset sizes in the current period tend to choose higher asset sizes in the next period. Moreover, banks choose lower asset sizes when the uncertainty of asset return is high.

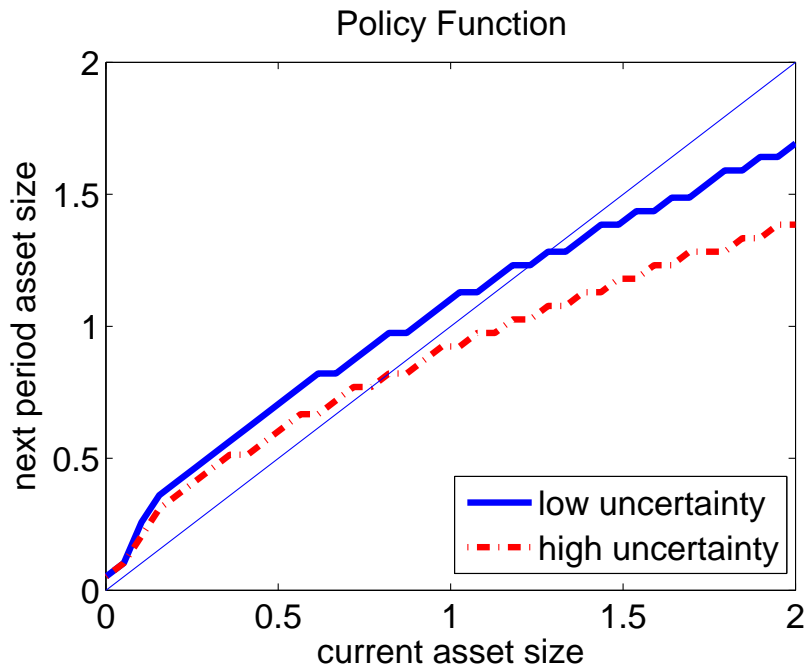
Figure 12 illustrates the interest spread schedule of risky debt. In the figure, the spread schedule for risky debt under low and high asset return uncertainty for a bank with mean idiosyncratic productivity,

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<sup>31</sup>Despite temporal variations, however, the general shape of the bank size distribution has been shown to be well described by a lognormal distribution with a Pareto tail (see Janicki and Prescott (2006) and Benito (2008)).

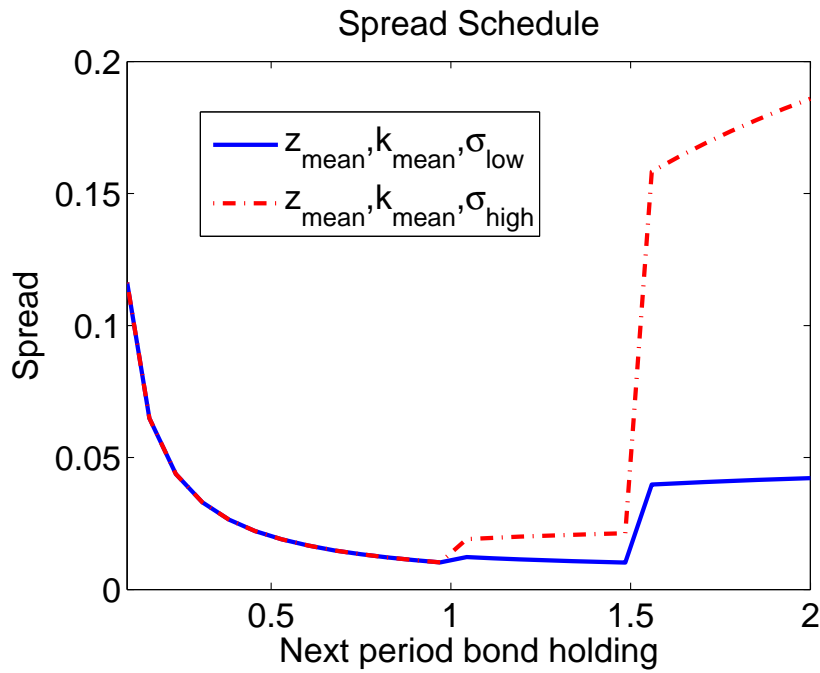


Figure 11: Policy Rules



Notes: This figure shows the optimal asset size choice as a function of the previous period asset size  $K$  for a bank with mean permanent asset return component  $a_i^3$ , stochastic shock and debt level. All values on the axis are relative to the average asset size of the  $a_i^3$  banks

Figure 12: Interest Spread Schedule



Notes: This figure shows the interbank interest spread as a function of the debt issuance for a bank with mean permanent asset return component  $a_i^3$ , stochastic shock and asset level. All values on the horizontal axis are relative to the average asset size of the  $a_i^3$  banks.

mean permanent productivity and mean asset size are plotted in blue solid and red dash-dot line respectively. Under the low asset return uncertainty regime, the bank can borrow up to 1.5 times of its asset without defaulting. When the uncertainty of asset return is high, bank faces higher interbank market spread. This is consistent with what is observed in the data and also with what I proved analytically in section 2. Large loans are expensive because of higher default risk. When debt level rises, the bank's default probability increases, hence the spread would also increase. Therefore, the spread schedule is upward sloping when the debt level is high. Small loans also have large effective interest rates due to the fixed credit cost. Fixed credit costs make borrowing very costly for banks with low debt. Hence, the spread schedule is downward sloping when the debt level is low.

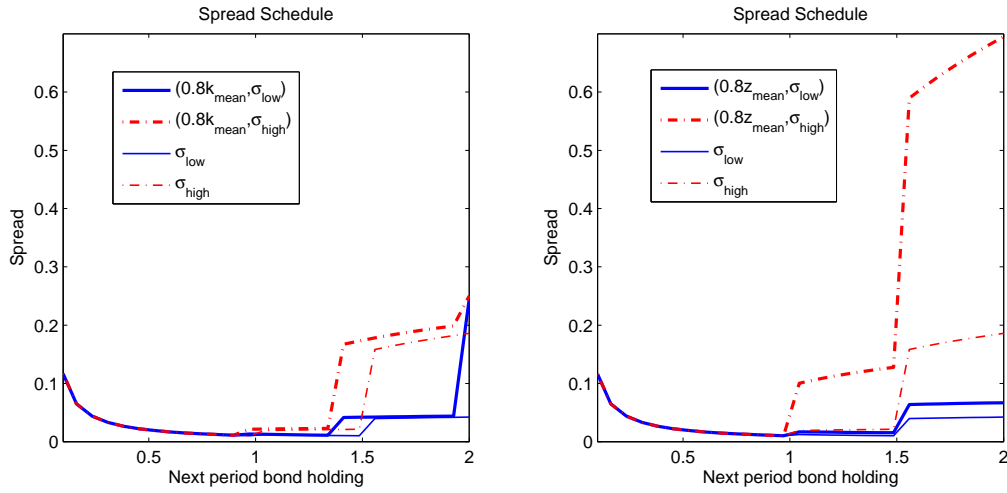
The left panel of Figure 13 shows the spread schedule of risky debt for bank's with a lower asset size under low and high asset return uncertainty, respectively. Interest spread is higher for banks with asset size that is 80% of average asset size. Asset return uncertainty's impact on spread is still positive. The right panel of Figure 13 shows the spread schedule of risky debt for bank's with lower asset return under low and high asset return uncertainty. Interest spread is lower for banks with an asset return that is 80% as large as average asset return. The impact of asset return uncertainty on interest spread is still positive.

Figure 14 illustrates the default and non-default regions for bank's with different asset sizes and debt level. Banks with higher asset sizes have lower default probability. A bank's default probability increases when it issues more bonds. Also, bank default probability increases under higher asset uncertainty. As shown in the figure, the red default area expands when the uncertainty of asset return increases. This indicates that the banks would be more likely to default.

#### 4.3.2 Regression: Model vs. Data

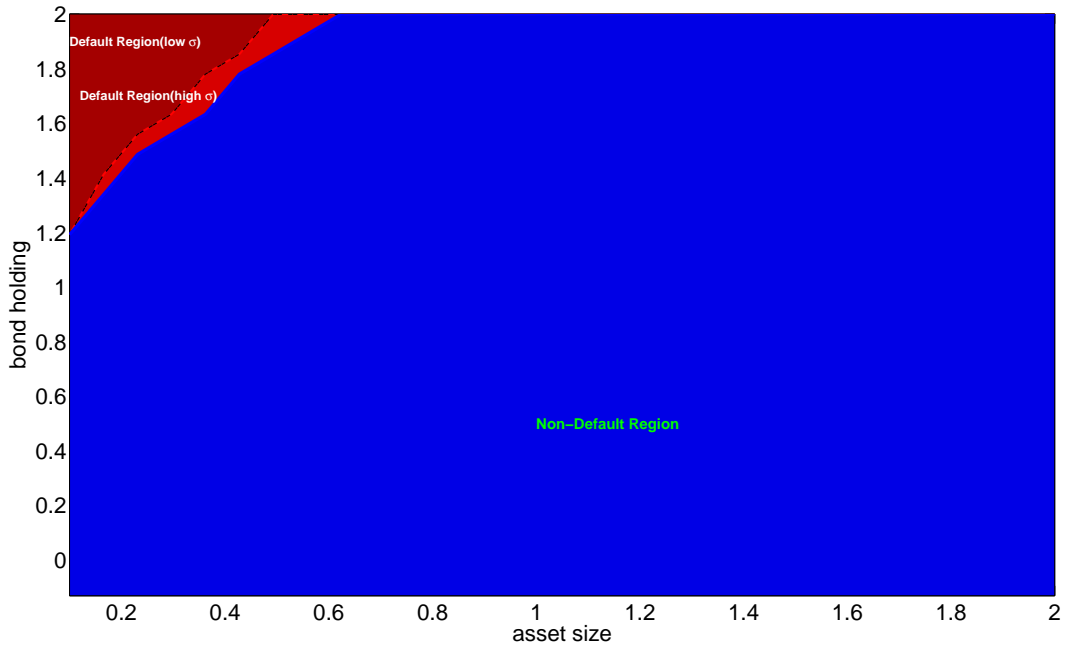
I simulate the model for 100,000 banks for 200 periods. The model delivers a simulated bank panel. Then I randomly draw 281 banks from this simulated panel. Using the simulated bank panel data, I run the same regression as I did in section 1 to check if the model's implications match the data. Both regressions control for bank fixed effects. The results are reported in Table 6. The regression can be viewed as an out-of-sample test of the model given that they are not targeted in the estimation. The model generates similar positive correlation between leverage and asset size, and negative correlation between asset return uncertainty and leverage. When asset return uncertainty increases by 1%,

Figure 13: Spread Schedule Comparison



Notes: The left panel shows the interbank interest spread as a function of the debt issuance for a bank with mean permanent asset return component  $a_i^3$ , stochastic shock and 80% of mean asset level at across the  $a_i^3$  banks. The right panel shows the interbank interest spread as a function of the debt issuance for a bank with mean permanent asset return component  $a_i^3$ , asset level and 80% of mean stochastic shock across the  $a_i^3$  banks. All values on the axis are relative to the average asset across the  $a_i^3$  banks.

Figure 14: Default Region



Notes: The figure depicts the default and non-default regions of a bank with median permanent asset return component  $a_i^3$  and stochastic shock. All values on the axes are relative to the average capital across the  $a_i^3$  banks.

leverage decreases by 0.0177 percentage point in the data, and by 0.0161 percentage point in the model. When asset size increases by 1%, leverage increases by 0.0268 percentage point in the data, by 0.0414 percentage point in the model.

Table 6: Regression: Model v.s Data

VARIABLES	Model <i>leverage<sub>it</sub></i>	Data <i>leverage<sub>it</sub></i>
$\log(asset_{it-1})$	0.0414*** (0.0094)	0.0268*** (0.0049)
$\log(gross\ asset\ return_{it-1})$	-0.1120* (0.0704)	-0.2302*** (0.0431)
$\log(gross\ asset\ return\ uncertainty_{t-1})$	-0.0161*** (0.0012)	-0.0177*** (0.0032)
Fixed effect	✓	✓
$R^2$	0.3101	0.2621

Notes: Standard errors in parentheses. Standard errors of simulated data regression are calculated using the bootstrapping method. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

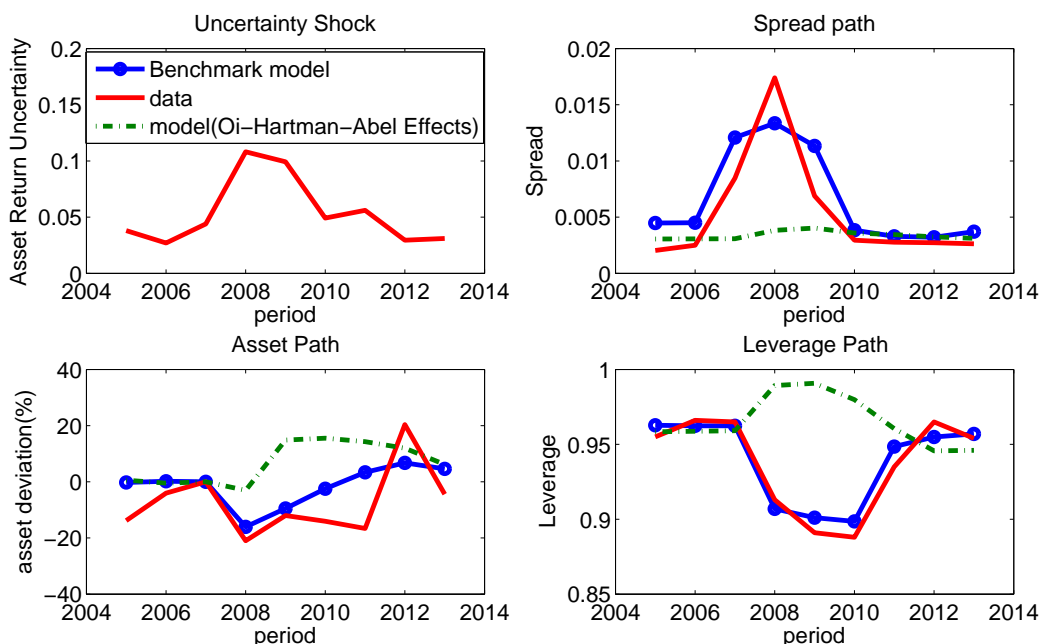
### 4.3.3 Event Study: Modeling the 2007-2009 Financial Crisis

The 2007-2009 financial crisis can be modeled as a decrease in asset returns, or an increase in asset return uncertainty. In this paper, I first focus on the impact of an increase of bank asset return uncertainty. I fit the empirical observed asset return uncertainty to the model and resolve the model. Given a sequence of measured asset return uncertainty shocks exactly as observed in the data, the responses of the modeled economy are shown in Figure 15.

In Figure 15, the data and simulated paths by the benchmark model are shown in solid line and line with circle respectively. I normalize the total asset by calculating the percentage deviation from its base value at year 2007 when the crisis started. In response to the uncertainty shock, bank asset size shrinks by around 20%, similar to what is observed in the data. But bank assets in the model recover faster than that in the real data. The evolution path of leverage generated by the model tightly matches the data. Mean leverage decreases from around 0.96 to around 0.89, both in the model and in the data. The increase of uncertainty raises the external financing cost and the probability of costly firesale, thus the banks decrease their leverage to lower their expected default probability and financing costs. I also examine the responses of the economy under no quadratic asset adjustment or

firesale costs. The results are plotted in dotted lines. When asset return uncertainty increases, the total asset actually increases. This result is related to the [Oi \(1961\)](#), [Hartman \(1972\)](#) and [Abel \(1983\)](#) effect. When there is no adjustment cost of any type in the economy, banks would take advantage of the uncertainty shock by adjusting their sizes freely: banks with good asset return shocks would increase their asset sizes, whereas banks received low asset return shocks would shrink their asset sizes. The redistribution might result in an increase of the aggregate asset level. By comparison, when we add quadratic adjustment costs and firesale costs of assets to the model, the real option effect dominates in the short run and results in a decrease in the asset size and the leverage ratio.

Figure 15: Event Study: Model v.s Data



Notes: The figure depicts the simulated evolution paths of total asset, aggregate leverage ratio, and mean interest spread of shadow banks in response to the asset return uncertainty shocks compared with their data counterparts. Leverage is defined as total debt to total asset ratio. The data and simulated paths by the benchmark model are shown by the solid line and line with circle respectively. The dotted line depicts the evolution path of the asset, leverage and interest spread assuming there is no firesale cost or asset adjustment cost such that Oi-Hartman-Abel effects dominates the real option effect.

Figure 15 also shows the simulated path of the interbank spread. The spread increases when uncertainty increases, as observed in the data and proved in the Section 2. The data for interbank spread is calculated by taking the yearly average of the daily TED spread. The interbank spread spikes up by around 1.3 percent, smaller than what observed in the data. That is because in the data the spread also includes an extra risk premium that results from people's risky averse utility function.

Under the Oi-Hartman-Abel case, because there is no quadratic asset adjustment or firesale costs, the banks adjust their leverages and asset sizes very quickly, thus lowering their default probability. Therefore, the interbank spread barely increases.

I calculate the statistics for the non-crisis periods and crisis period. Following Bloom et al. (2012), normal periods are defined as from 2005 to 2006 and 2010 to 2013, crisis periods are defined as from 2008 to 2009. The statistics comparison are shown in Table 7.

Table 7: Statistics: Model v.s Data

Panel A:				
	normal periods		crisis periods	
	model	data	model	data
default probability	0.008	0.007	0.018	0.019
spread	0.005	0.004	0.013	0.016
leverage	0.961	0.969	0.891	0.895

Panel B:			
	Model	data	
Correlation	spread	spread	
default probability	0.85	0.91	
leverage	-0.69	-0.42	

Panel C:			
	Model	data	
Aggregate leverage change	0.070	0.074	
Extensive margin	57%	61%	
Intensive margin	43%	39%	

Notes: This table shows the simulated statistics of shadow banks compared with their data counterparts. Leverage is defined as total debt to total asset ratio. Panel A shows the mean value of default probability, spread and leverage respectively. Panel B shows the correlation between expected default probability of bank. Panel C show the contribution of intensive margin and extensive margin to aggregate leverage ratio respectively. Extensive margin is defined as the change of aggregate leverage resulting from change of bank's asset distribution. Intensive margin is defined as the change of aggregate leverage resulting from bank of all asset quantiles take a lower leverage, given a fixed asset distribution.

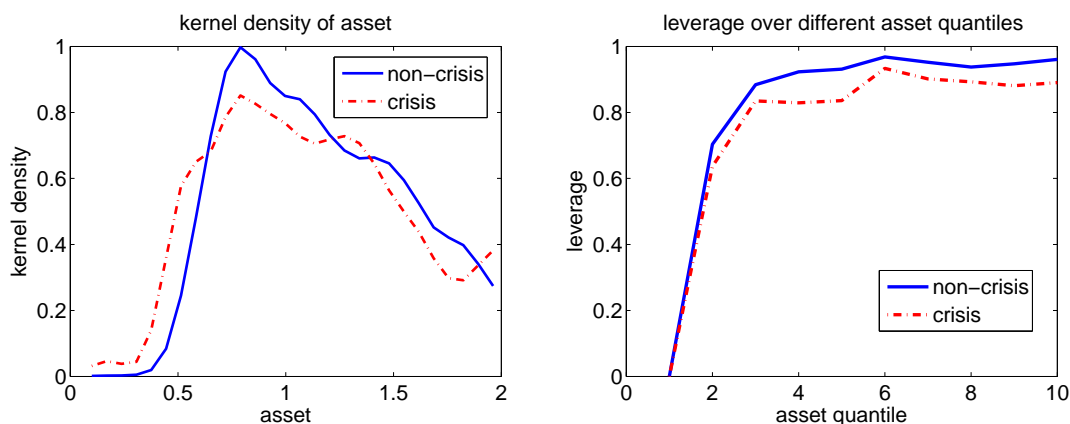
Panel A of Table 7 shows the mean value of the default probability, the spread and the leverage. The statistics generated by the model match the data closely. Panel B of Table 7 shows the correlation between expected default probability<sup>32</sup> and interbank spread. I find that interbank market spread is positively correlated with bank default probability and is negatively correlated with the bank leverage.

<sup>32</sup>The default probability of banks in the data is estimated by bankruptcy frequency in the dataset. The BankScope and WorldScope database provide detailed information about the date at which a bank becomes inactive. When a bank files for Chapter 7 or Chapter 11 for bankruptcy, it is labeled as inactive. The bank default probability in a given year is calculated as the number of banks that become inactive divided by the total number of banks in that year.

The magnitudes of correlations generated by the model is close to those observed in the data. Panel C of Table 7 shows the proportion of aggregated leverage change which can be attributed to extensive margin (banks are distributed more densely at lower asset level) and intensive margin (banks on different asset quantiles employ lower leverage). In both the model and the data, a larger portion of aggregate leverage change can be attributed to the extensive margin. The model over-predicts the intensive margin by merely 4%.

I also find that the model can generate a similar pattern for the change of leverage schedule over different asset quantiles and asset distribution. The left panel of Figure 16 shows the asset distribution in non-crisis periods and crisis periods. Banks reduce their size such that the whole distribution of assets would skew more to the left in the crisis, similar to our empirical observation. The right panel of Figure 16 shows the change of leverages over different asset quantiles. Consistent with what is observed in the data, banks with higher asset sizes employ a higher leverage. During a crisis, banks of different asset quantiles generally employ a lower leverage.

Figure 16: Asset Distribution and Leverage over different Asset Quantiles



Notes: This figure depicts the simulated asset distribution and leverage schedule over different asset quantiles based on the simulated bank panel. Crisis periods are defined as the periods with high asset return uncertainty value. The rest of the periods are defined as non-crisis periods.

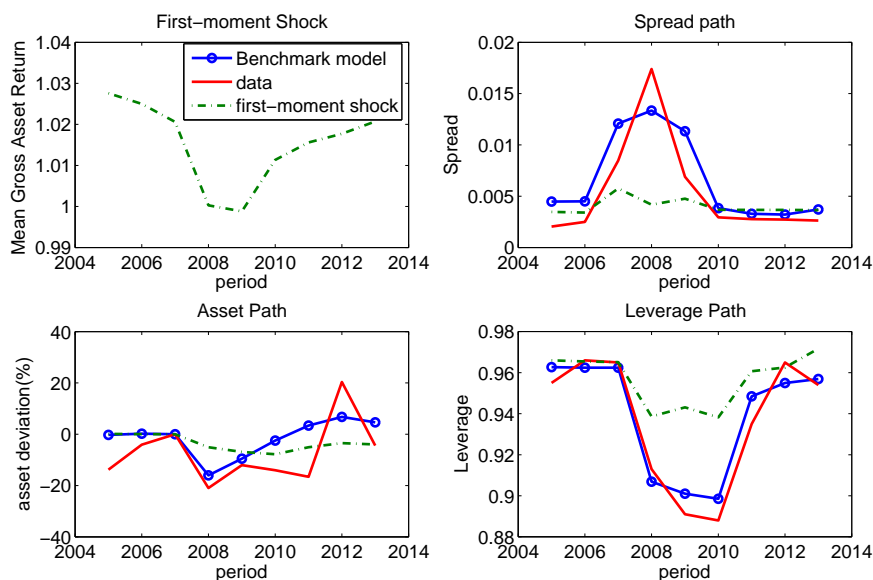
To test if a purely first-moment shock can also generate similar impacts on interbank spreads, bank asset sizes and leverages, I solve and reestimate an alternative model with a purely first-moment shock<sup>33</sup>. I assume the risky loan gives the bank the gross return  $A_t z_t k_t$ .  $z_t$  is the idiosyncratic gross rate of return on the bank asset.  $A_t$  is an aggregate state variable that captures the mean asset return rate of the economy. I impose the aggregate uncertainty of the bank return constant, fit the

<sup>33</sup>Shocks to the level of profit.

empirical observed mean asset return to the model, and resolve the model. Given a sequence of measured mean asset return exactly as what observed in the data, the responses of the moments to a purely first-moment aggregate asset return shock are shown in Figure 17. The model with purely first-moment shocks can only explain less than 30% of the change in the interbank spread, leverage, and asset size of the U.S. shadow banking sector.

To further check if a model without maturity mismatch can also generate similar impacts on interbank spreads, bank asset sizes and leverages, I solve and reestimate an alternative model without maturity mismatch. The simulated pathways of spread, asset, and leverage are shown in Figure 18. The model without maturity mismatch can only explain around 30% of the change in the interbank spread, leverage, and asset of the U.S. shadow banking sector.

Figure 17: Event Study: Model(Pure first-moment shocks) v.s Data

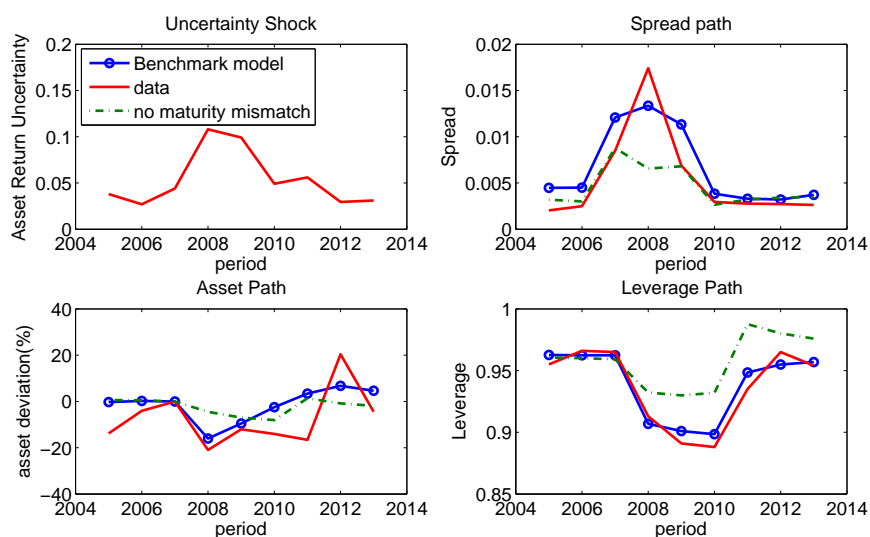


Notes: The figure depicts the simulated evolution paths of total asset, aggregate leverage ratio and mean interest spread of shadow banks in response to the first-moment (level) shocks compared with second moment (uncertainty) shocks and their data counterparts. Leverage is defined as total debt to total asset ratio. The data and simulated path by the benchmark model are shown in solid line and line with circle respectively. The dotted line depicts the evolution path of the asset, leverage and interest spread in response to a purely first-moment shock.

I reestimate the model under the following three specifications: model with purely first-moment shock, model without firesale cost, and model without maturity mismatch. Table 8 reports the estimation results. Models with these alternative specifications tend to underestimate the standard deviation of leverage, asset growth rate, and default probability and overestimate the mean leverage. The over-identification tests fail to reject the baseline model with a  $p$ -value of 0.6491. The simulated



Figure 18: Event Study: Model(No Maturity Mismatch) v.s Data



Notes: The figure depicts the simulated evolution paths of total asset, aggregate leverage ratio and mean interest spread of shadow banks in an alternative model without maturity mismatch compared with the baseline model and their data counterparts. Leverage is defined as total debt to total asset ratio. The data and simulated path by the benchmark model are shown in solid line and line with circle respectively. The dotted line depicts the evolution path of the asset, leverage and interest spread in a model without maturity mismatch.

moments are not statistically significant different from the actual moments, hence the baseline model is valid. The tests reject the model with purely first-moment shock, the model without firesale costs, and the model without maturity mismatch at the significance level of 5%.

#### 4.4 Policy Experiment: Debt Guarantee and TARP

In this section, I extend the baseline model to further study the effects of government intervention. In the 2007-2009 financial crisis, because the nominal interest rate dropped to zero, to stimulate the economy, the Federal Reserve took drastic unconventional monetary policies, including directly lending, Troubled Asset Relief Program (TARP), and debt guarantee, etc. One strand of literature led by [Gertler and Kiyotaki \(2010\)](#) analyze the effect of unconventional monetary policies on the real economy ex post. At the same time, a growing theoretical literature investigates the moral hazard caused by the government bailout. When considering moral hazard, government intervention can be severely counterproductive. Once forming the expectation of government bailout, banks might act even more recklessly and this might even lead to a vicious cycle. In this section, I analyze the effects of two government policies: the Troubled Asset Relief Program(TARP) and debt guarantee.

Table 8: Moments across Alternative Model Specifications

Target Moments	Actual Moments	Baseline Model	First-moment Shock	No Firesale Cost: $\zeta = 1$	No Maturity Mismatch: $\delta = 1$
mean of leverage	0.9541	0.9489	0.9952	1.0984	1.1965
Std of leverage	0.1917	0.1312	0.0131	0.0247	0.0178
autocorrelation of leverage	0.8514	0.6874	0.6954	0.6844	0.6021
mean of asset growth	0.0447	0.0378	0.0119	0.0088	0.0767
Std of asset growth rate	0.0035	0.0142	0.0005	0.0012	0.0001
autocorrelation of asset growth rate	0.8997	0.9409	0.9788	0.8544	0.8730
mean default rate	0.0110	0.0098	0.0011	0.0028	0.0047
mean of dividend/asset ratio	0.0214	0.0369	0.0751	0.0485	0.0652
Std of dividend/asset ratio	0.0145	0.0019	0.0004	0.0027	0.0035
autocorrelation of dividend/asset ratio	0.7949	0.8532	0.9433	0.8104	0.7548
mean entrant leverage	0.9718	0.9945	0.9957	0.9844	1.0142
mean entrant growth	0.2417	0.1007	0.3014	0.2412	0.2578
IQR(75/25) leverage slope	1.1715	1.1954	1.0401	0.9215	0.9521
J-statistics		0.2070	4.3453	5.9981	6.0514
P-value		0.6491	0.0371	0.0498	0.0485

Notes: Calculations are based on an annual sample of shadow banks from the BankScope and WorldScope database. The estimation is done with SMM, which chooses model parameters by matching the moments from a simulated panel of banks to the corresponding moments from the data. J-statistics tests the over-identification constraint for the moment conditions.

Firstly, I consider the impact of TARP. The U.S. government announced the Troubled Asset Relief Program (TARP) during the recent financial crisis. Under TARP, the U.S. Treasury provided capital to 736 financial institutions of all sizes across the country. The total rescue funds are around 200 billion, around 4.39% of bank's total asset. The Federal Reserve took some nonstandard procedures such as extending the range of collateral a bank could use to borrow from the central bank, and the exchange of illiquid assets by liquid assets. We model TARP in the following way: the government would purchase a certain fraction of a bank's long-term assets at full value, such that the bank can avoid part of the asset firesale costs. The balance sheet of the bank under TARP is shown in the following table.

Assets	Liabilities
Long-term asset $(1 - \delta)k_t - G_t$	Net worth $n_t$
$G_t$	
Cash flow $z_t k_t - (1 - \delta)k_t$	Risky debt $b_t - q_t b_{t+1}$

where  $G_t = \xi^g(b_t - q_t b_{t+1} - z_t k_t + (1 - \delta)k_t)$ ,  $\xi^g$  is the fraction of cash shortage replenished by the government, and  $\xi^g$  is calibrated to match the fraction of total government rescue fund in total assets.

After government intervention, the bank still need to firesale  $\frac{(1-\xi^g)(b_t - q_t b_{t+1} - z_t k_t + (1-\delta)k_t)}{\zeta}$  amount of its long-term asset to pay the debt due, the total amount of long-term asset left after the firesale is  $(1 - \delta)k_t - G_t - \frac{(1-\xi^g)G_t}{\zeta\xi^g}$ . The constraint of banks becomes:

$$e = (1 - \delta)k_t - G_t - \frac{(1 - \xi^g)G_t}{\zeta\xi^g} - k_{t+1}. \quad (21)$$

Second, I analyze the impact of debt guarantee. During the recent financial crisis, the government also announced a debt guarantee for new short and medium term debt issued by eligible institutions in case a bank default. I examine the impact of this program by making the lender in the interbank market take into consideration the possibility that the government will guarantee the debt of the bank in case of default. This formulation is in the same spirit as the "third-party bailout" in Aguiar and

Gopinath (2006)<sup>34</sup>.

Then the price schedule for risk debt can be written as follow:

$$\begin{aligned}
q(z, k', b'; \sigma) = & \frac{1 - \iint d(z', k', b'; \sigma') f(z'|z, \sigma') g(\sigma'|\sigma) d\theta d\sigma}{1 + r} \\
& + (1 - p) \frac{\iint d(z', k', b'; \sigma') R(z', k', b') f(z'|z, \sigma') g(\sigma'|\sigma) dz d\sigma}{(1 + r)b'} \\
& + p \frac{\iint d(z', k', b'; \sigma') f(z'|z, \sigma') g(\sigma'|\sigma) dz d\sigma}{1 + r} - \frac{\xi}{b'}. \tag{22}
\end{aligned}$$

Since the bank could be bailed out by the government after it chooses to default, its default value is no longer zero. After taking into account the government bailout, the default value for the bank becomes:

$$V^d = pV^c(z, k, 0, \sigma). \tag{23}$$

I take into consideration bank's moral hazard by modeling banks with larger assets having a higher probability of receiving debt guarantee. I assume the bailout probability  $p$  is endogenously determined by the bank's size and asset return. In particular, assuming that the bailout probability is an increasing function of the bank's size  $k$  and its asset return  $z$ :  $p = \varsigma z^\chi k^{1-\chi}$ . Then I compare the statistics under endogenous bailout and exogenous bailout. The expected bailout probability of these two types of bailout strategies are the same. The difference is that, in the case of exogenous bailout, the government literally chooses which banks to bailout by lottery, whereas in the case of an endogenous bailout probability, government bailout the banks with larger assets with higher probability.

I compare the different effects of debt guarantee and TARP on default rate, leverage, interbank spread, and market liquidity<sup>35</sup>. The results are shown in Table 9. In Table 9, two government interventions are chosen such that the total government resources used in each case are equal. Under debt guarantee, two bailout probability strategies are chosen such that the expected bailout probabilities are the same in two cases. The first column shows the statistics under no government policy. The second column corresponds to asset purchase of 5% of total bank assets under TARP. The

<sup>34</sup>In the 2007-2009 financial crisis, the U.S government bailed out some financial institutions and let others file for bankruptcy without further aid. It rescued Bear Sterns by subsidizing its merger with JP Morgan Chase&Co. It injected capital directly into 736 financial institutions, it also let many financial institutions file for bankruptcy including Lehman Brothers.

<sup>35</sup>The total liquidity is calculated as the sum of assets of all non-default banks in the market, and the unit is  $10^6$ . It inherently captures the size of credit intermediation by shadow banks.

Table 9: Government Policy Comparison

	No Policy	TARP	Debt Guarantee	
			exogenous bailout	endogenous bailout
mean spread	0.013	0.011	0.010	0.034
mean leverage	0.954	0.975	0.977	0.989
mean default rate	0.018	0.012	0.024	0.037
total liquidity	1.708	2.111	2.014	1.801

Notes: This table shows the simulated statistics of shadow banks using simulated bank panel under different government policies. TARP is modeled as the government purchases a certain fraction of bank's long-term asset at full value, such that the bank can avoid part of the costs of a firesale. Debt guarantee is modeled as the government bails out a bank with certain probability if a bank defaults. Bailout probability is the same for all banks under the exogenous bailout case and is an increasing function of bank asset size under the endogenous bailout case.

third and fourth columns correspond to expected government bailout probability of 23% in case the bank defaults. This is obtained when I set  $\varsigma = 0.395$  and  $\chi = 0.4$ .

As shown in Table 9, given government intervention strategies, the banks would choose higher leverage ex ante on average. Under TARP, because banks partly avoid costly firesale, the banks' default probability is lower. Thus, they face lower spreads than the no policy case. However, the banks would employ a slightly higher leverage compared with the no policy case. Under the debt guarantee intervention, when the bailout probability is set as an increasing function of bank size, a bank would employ a higher leverage than in the exogenous bailout case. The reason is that a bank would tend to employ a higher leverage to build a bigger "empire" to take advantage of government bailout. The implication is that it might be optimal to make uncertainty as a commitment. The uncertainty of government bailout makes the bank more cautious, avoiding to be the worst performer and exposing itself to the risk of not getting bailed out. Also, notice that under debt guarantee, although the default probability of banks is higher, because of government debt guarantee, the spread the bank faces is actually lower than the no policy case. Under debt guarantee, the total liquidity in the market is higher because banks employ higher leverage. However, since the bank default rate is higher under debt guarantee, the total liquidity of the market is lower than that under the TARP. In particular, under the endogenous bailout case, although the total liquidity is higher than the no policy case because banks employ higher leverages, it is lower than the TARP or exogenous bailout case because banks default with higher probability. Debt guarantees with endogenous government bailout have a much more deleterious effect on bank behavior because they raise the value of equity in times of default

and thus engender risk-shifting activities.

## 4.5 Counterfactuals

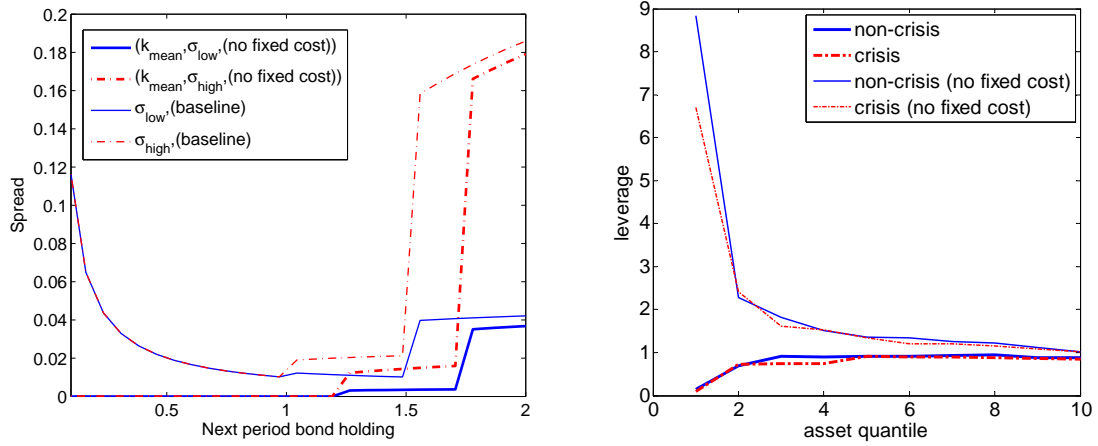
I now examine the default, financing and investment decisions of banks provided that banks had different fundamental characteristics than those implied by the parameters estimates from Table 5. To this end, I first consider a baseline model without fixed credit cost. The interest spread schedule and the leverage schedule under no fixed credit cost are shown in Figure 19. Without fixed credit cost, banks face lower interest spreads. Banks experiencing sequence of bad asset return shocks would choose to reduce their scale to avoid costly equity issuance and increase their debt financing, climbing up their debt schedules. Thus the leverage schedule over asset would be counterfactually downward sloping. With fixed credit costs, it is much more costly for small banks to issue small amounts of debt, thus they would tend to employ lower leverages.

I also model financial innovation as the change of fixed credit cost to estimate the contribution of financial innovation to risk building of the U.S. shadow banking system before the 2007-2009 financial crisis. This is in the same spirit as [Quadrini \(2015\)](#). I estimate the model on the subsamples of data from 1999 to 2004 and from 2007 to 2013, respectively. Then I keep other parameters unchanged, and change the fixed credit parameter to its average value during the 1999-2004 period. By doing this, I find that the aggregate leverage of the U.S. shadow banking sector would have been 0.941 in 2007 if the fixed credit cost were as high as it was during the period from 1999 to 2004. To the extent that other factors remain constant, financial innovation alone contributes to 44% of the increase of aggregate leverage in the U.S. shadow banking sector. Other factors contribute to the build up of risk, as argued in the literature, might be the change of interest rate driven by the increasing foreign demand for the U.S. risk-free assets, and the change of SEC regulations on shadow banking in 2004.

I then consider the impact of a higher degree of maturity mismatch. The results are shown in Figure 20. Because a higher degree of maturity mismatch would increase the probability of a costly firesale, banks would be more cautious and banks over all asset quantiles tend to use lower leverage in crisis-period compared with non-crisis periods. Higher maturity mismatch also increases the change of interest spread in the interbank market.

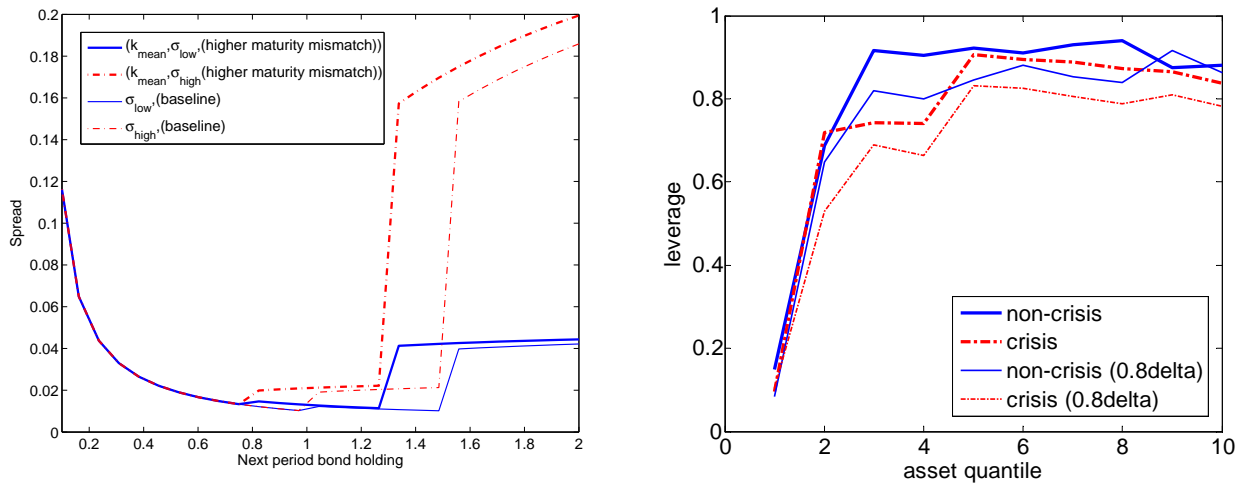
Finally, I show the comparative statics of the impact of changing the parameters that govern

Figure 19: Interest Spread Schedule and Leverage Schedule under no fixed credit cost



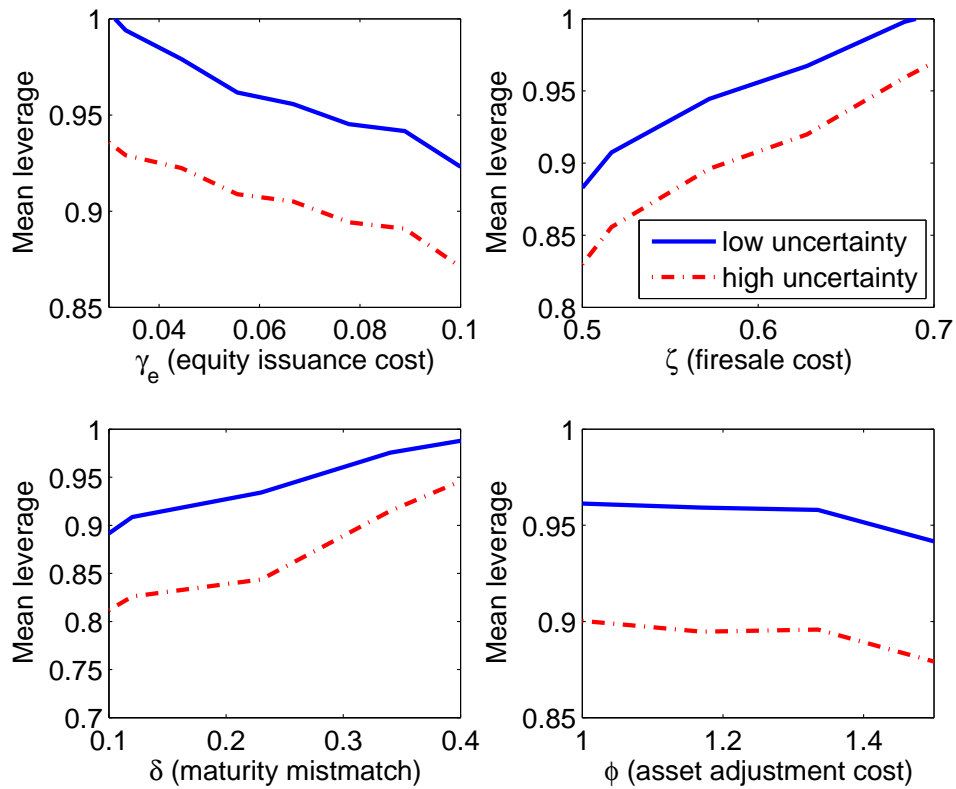
Notes: This figure depicts the counterfactual spread schedule and leverage schedule over different asset quantiles based on the bank panel data simulated assuming that there is no fixed credit cost. Crisis periods are defined as the periods with high asset return uncertainty. The rest of the periods are defined as non-crisis periods.

Figure 20: Interest Spread Schedule and Leverage Schedule under greater maturity-mismatch



Notes: This figure depicts the counterfactual spread schedule and leverage schedule over different asset quantiles based on the bank panel simulated assuming that the degree of maturity mismatch is 80% of the estimated value. Crisis periods are defined as the periods with high asset return uncertainty. The rest of the periods are defined as non-crisis periods.

Figure 21: Mean leverage Comparative Statics



Notes: This figure depicts aggregate leverage ratio comparative statics under different parameter settings. For each panel, I solve and simulate the model 20 times, each time corresponding to a different value of the parameter in question. For each of these 20 simulations, I calculate the mean leverage over the 100,000 simulated time periods. The mean leverage under low uncertainty state and high uncertainty state are shown in solid blue line and red dotted line respectively.



equity issuance cost, firesale cost, maturity mismatch, and asset adjustment cost on mean leverage of banks. The results are shown in Figure 21. The results of the model are robust across a wide range of parameter settings. To construct each panel, I change one parameter at a time while keeping other parameters unchanged as estimated in the benchmark model. For each panel, I solve and simulate the model 20 times, each time corresponding to different value of the parameter in question. For each of these 20 simulations, I calculate the mean leverage over the 100,000 simulated time periods. I find that the result that mean leverage is lower when the economy is in a high uncertainty state is robust across a wide range of parameter setups. When I increase the equity issuance cost, the mean leverage of the economy decreases. Banks would be more cautious, employing a lower leverage to reduce the probability of costly equity issuance. The higher the firesale cost parameter  $\zeta$ , the higher the fraction of value the bank can get from the firesale of its asset. Because firesale becomes less costly, banks are more willing to take higher leverage. The higher the maturity mismatch parameter, the lower the degree of the bank's asset and liability maturity mismatch. The probability of costly asset fire sale would decrease and thus banks employ higher leverages on average. Also the change of mean leverage from low to high uncertainty state would be smaller. Increasing asset adjustment costs raises the cost for banks to adjust assets when hit by unfavorable shocks. Thus, in general, banks would employ lower leverage when the adjustment cost increases.

## 5 Conclusion

In this paper, I examine the impact of asset return uncertainty on the financing and leverage decisions of shadow banks. I first document several stylized facts of the U.S. shadow banking industry using a detailed micro-level dataset. Then I contribute to the literature by being the first in building a quantitative model with heterogeneous banks, endogenous bank default, aggregate uncertainty fluctuation and maturity mismatch to characterize the shadow banking dynamics in a full nonlinear manner. Moreover, I estimate the model using a comprehensive micro-level shadow banking dataset to quantify the impacts of time-varying uncertainty and financial frictions in this sector. I show that when the uncertainty of bank asset return increases and interbank spread spikes up, shadow banks would employ a lower leverage to lower their default probability and reduce financing costs. This leads to a contraction in the credit intermediation. I find that uncertainty shocks are able to generate statistics

closely match the data and explain over 90% of deleveraging and asset contraction in U.S shadow banking industry. High maturity mismatch and firesale costs amplify the impact of uncertainty shocks. Alternative model settings with only pure first-moment shocks, without asset firesale costs, or without maturity mismatch, can at most explain around one-third of the changes in the interbank spread, leverage, asset size of the U.S. shadow banking sector. I also analyze the impact of unconventional monetary policies. The finding suggests that unconventional monetary policies can help dampen the liquidity contraction. However, after taking into account bank moral hazard, I find that government bailout might be counterproductive.

The paper also contributes to the literature for its strong policy implications. First, to counter the credit contraction, only maintaining the average asset return above a certain level is insufficient, certain measures<sup>36</sup> should be taken to contain the asset return uncertainty since it plays a more important role in affecting the size of shadow banking. Second, since maturity mismatch and firesale cost amplify the impacts of adverse shocks, to counter the rise in interbank spread and stabilize the credit intermediation, certain measures should be taken to restrict the degree of maturity mismatch and reduce the cost of asset firesale. Third, when carrying out unconventional monetary policies, the government should take into account the potential cost incurred by bank moral hazard.

To keep the analysis tractable, I have focused on a stylized model that abstracts from some realistic features in the actual economy. For example, I did not include firm sector and traditional banking sector in the model. Generalizing the model to incorporate firm sector and traditional banking sector is clearly desirable and is left for future research. Such generalization would make the model more empirically relevant for studying the role of financial intermediary leverage in propagating macroeconomic fluctuations, as shown by [Liu, Wang, and Zha \(2013\)](#) and [Christiano et al. \(2014\)](#). The key mechanism of the model, however, is likely to carry over to a model with more realistic features.

In this paper, I focus on understanding the impact of asset return uncertainty on financing and leverage decisions of shadow banks. When analyzing the impact of unconventional monetary policy, I abstract from the direct cost of these policies. An important direction for future research is to study optimal fiscal and monetary policy interventions in the presence of bank moral hazard. The bailout probability in the model is still exogenous in the sense that the I have not explicitly modeled a

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<sup>36</sup>Potential policy remedies include stress tests on the shadow banking system ex ante to contain the riskiness of the bank asset portfolio and ex post government interventions to restrict asset price movements.

government that chooses this probability endogenously. Moreover, I have not explored what policies governments should take ex-ante to avoid excessive risk-taking. A mix of ex-ante macro-prudential policy and ex-post interventions may serve the optimal purpose of banking regulation. Future research along these lines should be both promising and fruitful.

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## Appendix

### A Computation Algorithm:

1. Discretize a finite state space for the four state variables:  $\{z, k, b; \sigma\}$ . The gross asset return rate and asset return uncertainty are discretized according the method proposed by [Tauchen and Hussey \(1991\)](#).
2. Take as given the risk-free interest rate, and assume an initial price function  $q^0(z, k, b; \sigma)$ . Use this  $q^0$  and solve for the maximization problem of banks using value function iteration.
3. Update the price function as  $q^1$  and solve for the bank's problem. Repeat step 2 and 3 until the distance between value function and price schedule is sufficiently close . Obtain the policy function.
4. Using the policy function, simulate a data panel of  $(KN, T + 100)$ , where  $K$  is a strictly positive integer denoting the number of simulated panel datasets,  $N$  is the number of banks in the actual data,  $T$  is the time dimension of the simulated data. Estimate the parameters by simulated methods of moments (SMM).

### B SMM Estimation

The fraction of the loan due each period  $\delta$ , equity issuance cost  $\gamma_e$ , firesale cost  $\varsigma$ , parameters governing aggregate shocks  $\rho_\sigma, \mu_\sigma, \varphi$ , the adjustment cost  $\phi$ , the persistence of asset return  $\rho_v$ , credit fixed cost  $\xi$ , entrant start-up asset  $k_0$ , and two more parameters govern the Pareto distribution of the permanent productivity are jointly determined to matched 13 moments: the mean value of default rate, the mean, the standard deviation and the auto-correlation of leverage, asset growth rate and the dividend to asset ratio of shadow banks and the mean leverage and growth of new entrant banks and the slope of the leverage schedule using simulated methods of moments(SMM), which minimizes a distance criterion between key moments from actual data. SMM procedes in the following way: For an arbitrary value of parameter vector  $\theta = \{\nu, A, \rho, \rho_\sigma, \mu_\sigma, \varphi, \phi, \xi, k_0, \gamma_e, \delta, \varsigma\}$ , the dynamic problem is solved and the policy functions are generated. Then I use the policy functions to simulate a data panel

of  $(KN, T + 100)$ , where  $K$  is a strictly positive integer denoting the number of simulated panel datasets,  $N$  is the number of banks in the actual data, and  $T$  is the time dimension of the simulated data. The first 100 periods are discarded so as to start from the ergodic distribution.

Let  $x_{it}$  be the actual data vector,  $i = 1, 2, \dots, N$ ,  $t = 1, \dots, T$ , and let  $y_{itk}(b)$  be the simulated vector from simulation  $k$ ,  $i = 1, 2, \dots, n$ ,  $t = 1, \dots, T$ , and  $k = 1, 2, \dots, K$ . The simulated data vector,  $y_{itk}(\theta)$ , depends on a vector of structural parameters,  $\theta$ . Define the moment conditions as:

$$\frac{1}{NT} \sum_{i=1}^n \sum_{t=1}^T \left[ h(x_{it}) - \frac{1}{K} \sum_{k=1}^K h(y_{itk}(\theta)) \right] \equiv \Psi^A - \Psi^S(\theta) \quad (\text{B.1})$$

where  $h(y_{itk}(\theta))$  is a vector of simulated moments and  $h(x_{it})$  is the actual data moments.  $\Psi^A = \frac{1}{NT} \sum_{i=1}^n \sum_{t=1}^T h(x_{it})$ ,  $\Psi^S(\theta) = \frac{1}{NTK} \sum_{i=1}^n \sum_{t=1}^T \sum_{k=1}^K h(y_{itk}(\theta))$

The simulated moments estimator is defined as the solution to the minimization of:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} [\Psi^A - \Psi^S(\theta)]' \hat{W} [\Psi^A - \Psi^S(\theta)] \quad (\text{B.2})$$

in which  $\hat{W}$  is a positive definite matrix that converges in probability to a deterministic positive definite matrix  $W$ . It is constructed by calculating the inverse of the variance-covariance matrix of the data moments. Define  $\Omega$  as the variance covariance matrix of the data moments  $\Psi^A$ . [Lee and Ingram \(2010\)](#) show that under the estimating null, the variance covariance of the simulated moments  $\Psi^S(\theta)$  is equal to  $\frac{1}{K}\Omega$ . Since  $\Psi^A$  and  $\Psi^S(\theta)$  are independent by construction,  $\hat{W} = [(1 + \frac{1}{K})\Omega]^{-1}$ .  $\Omega$  is calculated using influence function method following [Erickson and Whited \(2002\)](#).

I use a simulated annealing algorithm for minimizing the objective function. This starts with a predefined first and second guess. For the third guess onward, it takes the best prior guess and randomizes from this to generate a new set of parameter guesses. That is, it takes the best-fit parameters and randomly “jumps off” from this point for its next guess. Over time the algorithm “cools”, so that the variance of the parameter jumps falls, allowing the estimator to fine-tune its parameter estimates around the global best fit. I restart the program with different initial conditions to ensure the estimator converges to the global minimum. The simulated annealing algorithm is extremely slow, which restricts the size of the parameter space that can be estimated. Nevertheless, I use this because it is robust to the presence of local minima and discontinuities in the objective function across the parameter space.



The simulated moments is asymptotically normal for fixed  $K$ . Denote  $g(\theta) \equiv \Psi^A - \Psi^S(\theta)$ . The asymptotic distribution of  $\theta$  is given by:

$$\sqrt{n}(\theta - \hat{\theta}) \xrightarrow{d} N(0, \text{avar}(\hat{\theta})) \quad (\text{B.3})$$

in which

$$\text{avar}(\hat{\theta}) = \left(1 + \frac{1}{K}\right) \left[\frac{\partial g}{\partial \theta} W \frac{\partial g}{\partial \theta'}\right]^{-1} \left[\frac{\partial g}{\partial \theta} W \Omega W \frac{\partial g}{\partial \theta'}\right] \left[\frac{\partial g}{\partial \theta} W \frac{\partial g}{\partial \theta'}\right] \quad (\text{B.4})$$

in which  $\Omega$  is the probability limit of a consistent estimator of the covariance matrix. I calculate the estimate of this covariance matrix using influence function of the moment vector clustered at bank level following [Erickson and Whited \(2002\)](#).

## C Proofs

**Proposition 1:** Bank's leverage  $z^*$  decreases in its discount factor  $\beta$  and increases in floatation cost  $\chi$ . When the bank is sufficiently patient:  $\beta = \frac{\chi}{1+r}$ , it totally depends on internal (equity) finance ( $z^* = 0$ ).

**Proof:**

Denote

$$G(\beta, z^*) = z^* - \frac{1}{1-\theta} \left[1 - \frac{\beta(1+r)}{\chi}\right] \pi(z^*)^{-1} = 0,$$

Then by implicit function theorem

$$\frac{\partial z^*}{\partial \beta} = -\frac{\partial G/\partial \beta}{\partial G/\partial z^*} = -\frac{\frac{1}{1-\theta} \frac{(1+r)}{\chi} \pi(z^*)^{-1}}{1 + \frac{1}{1-\theta} \left[1 - \frac{\beta(1+r)}{\chi}\right] \pi(z^*)^{-2} \frac{\partial \pi(z^*)}{\partial z^*}}.$$

Note that:

$$\frac{\partial \pi(z^*)}{\partial z^*} = \frac{f'(z^*) [1 - F(z^*)] + f(z^*)^2}{[1 - F(z^*)]^2} > 0$$

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<sup>37</sup>For normal distribution,  $f'(z^*) [1 - F(z^*)] + f(z^*)^2 > 0$ . To see this, note that  $f'(z^*) [1 - F(z^*)] + f(z^*)^2 = f(z^*)(f(z^*) - z^* [1 - F(z^*)])$ . Denote  $g(z^*) = f(z^*) - z^* [1 - F(z^*)]$ . We only need to show  $g(z^*) > 0$ . Note that  $g(0) > 0$ ,  $\lim_{z^* \rightarrow \infty} g(z^*) = 0$ ,  $g'(z^*) = F(z^*) - 1 < 0$ , hence  $g(z^*) > 0$ .

Hence:

$$\frac{\partial z^*}{\partial \beta} < 0.$$

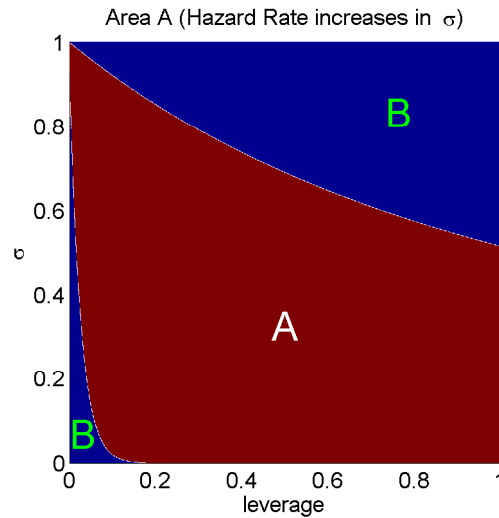
Similarly, it is trivial to show  $z^*$  increases in flotation cost  $\chi$ .

**Q.E.D**

**Proposition 2:** When the bank is sufficiently impatient:  $\beta < \frac{\chi}{1+r}$ , as long as the hazard rate is an increasing function of asset return uncertainty, i.e.,  $\frac{\partial \pi(z^*)}{\partial \sigma} > 0$ , leverage is a decreasing function of asset return uncertainty:  $\frac{\partial z^*}{\partial \sigma} < 0$ .

**Proof:**

Unfortunately, the hazard rate of log-normal distribution is not monotone in  $\sigma$ , which makes analytical solution for the range of parameters a nontrivial task. However, I find that under a wide range of parameters,  $\frac{\partial \pi(z^*)}{\partial \sigma} > 0$ <sup>38</sup>. As shown in the following graph, the hazard rate function of lognormal distribution is an increasing function of  $\sigma$  in Area A and a decreasing function of  $\sigma$  in Area B. Both the value of asset return uncertainty  $\sigma$  and mean leverage value  $z^*$  I estimated from the data<sup>39</sup> fall in Area A.



As long as  $\frac{\partial \pi(z^*)}{\partial \sigma} > 0$  and  $\frac{\beta(1+r)}{\chi} < 1$ <sup>40</sup>, it is trivial to show  $\frac{\partial z^*}{\partial \sigma} < 0$ .

<sup>38</sup>Statistically, hazard rate  $\pi(z^*)$  is the probability of observing an outcome within a neighborhood of  $z^*$ , conditional on the outcome being no less than  $z^*$ . For lognormal distribution, in a wide range of distribution parameters, when the volatility of the economy increases, this probability increases.

<sup>39</sup>See Figures 2, 6 and 7.

<sup>40</sup>The condition  $\frac{\beta(1+r)}{\chi} < 1$  requires that the bank is sufficiently impatient: its discount factor is smaller than  $\frac{\chi}{1+r}$ , so that the bank would choose to borrow.

Define:

$$H(z^*, \sigma) = z^* - \frac{1}{1-\theta} \left[ 1 - \frac{\beta(1+r)}{\chi} \right] \pi(z^*)^{-1},$$

Note that:

$$\frac{\partial \pi(z^*)}{\partial z^*} = \frac{f'(z^*) [1 - F(z^*)] + f(z^*)^2}{[1 - F(z^*)]^2} > 0$$

by the implicit function theorem, we have:

$$\frac{\partial z^*}{\partial \sigma} = - \frac{\partial H / \partial \sigma}{\partial H / \partial z^*} = - \frac{\frac{1}{1-\theta} \left[ 1 - \frac{\beta(1+r)}{\chi} \right] \frac{1}{\pi(z^*)^2} \frac{\partial \pi(z^*)}{\partial \sigma}}{1 + \frac{1}{1-\theta} \left[ 1 - \frac{\beta(1+r)}{\chi} \right] \frac{1}{\pi(z^*)^2} \frac{\partial \pi(z^*)}{\partial z^*}} < 0$$

**Q.E.D**

**Assumption 1:**  $\frac{1}{2} \operatorname{erfc}(\sqrt{\pi}) < \frac{\theta}{2} < \frac{\beta(1+r)}{\chi} < 1, 0 < z^* < 1.$

**Proposition 3:** The bank asset is a decreasing function of the asset return uncertainty:  $\frac{\partial k}{\partial \sigma} < 0.$

**Proof:**

From the first order condition with respect to  $k$ , denote

$$G(z^*, k, \sigma) = \frac{\chi}{1+r} \left[ \int_0^{z^*} z \theta dF(z) + z^* (1 - F(z^*)) \right] + \beta \int_{z^*}^{\infty} (z - z^*) dF(z) - 1 - \Psi'(k, 0)$$

After some algebra, it can be shown that:

$$\frac{\partial G}{\partial \sigma} = a_1 \left\{ \left[ 2\theta + \sqrt{z^*} e^{\frac{\sigma^4 + 4[\log(z^*)]^2}{8\sigma^2}} \operatorname{erfc}(\sqrt{\pi}) \right] \log(z^*) - \left[ 2 \frac{\beta(1+r)}{\chi} - \theta + \sqrt{z^*} e^{\frac{\sigma^4 + 4[\log(z^*)]^2}{8\sigma^2}} \operatorname{erfc}(\sqrt{\pi}) \right] \sigma^2 \right\},$$

where  $a_1 = \frac{\chi}{1+r} \frac{\sqrt{z^*}}{2\sqrt{2\pi}\sigma^2} e^{-\frac{\sigma^4 + 4[\log(z^*)]^2}{8\sigma^2}} > 0,$

Where  $\operatorname{erfc}$  is the complementary error function,  $\operatorname{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} e^{-t^2} dt, \operatorname{erfc}(\sqrt{\pi}) = 8.9696 \times 10^{-6} > 0,$

Under assumption 1,  $\frac{\partial G}{\partial \sigma} < 0.$

Also note that by F.O.C with respect to  $z^*$  ( equation (8)):

$$\frac{\partial G}{\partial z^*} = \left( \frac{\chi}{1+r} - \beta \right) [1 - F(z^*)] - \frac{\chi}{1+r} [(1-\theta)z^* f(z^*)] = 0.$$

Then by total differentiating  $G(z^*, k, \sigma) = 0$  with respect to  $\sigma$  on both sides, we get:

$$\partial k / \partial \sigma = - \frac{\frac{\partial G}{\partial \sigma} + \frac{\partial G}{\partial z^*} \frac{\partial z^*}{\partial \sigma}}{\partial G / \partial k} = \frac{\frac{\partial G}{\partial \sigma}}{\Psi''(k, 0)} < 0$$

**Q.E.D**

**Proposition 4:** The increase of asset return uncertainty increases the spread the bank faces when it issues debt.

**Proof:**

By

$$q = \frac{1}{1+r} \left[ \int_{z^*}^{\infty} dF(z) + \int_0^{z^*} \frac{z\theta}{z^*} dF(z) \right],$$

we have:

$$\frac{dq}{d\sigma} = \frac{\partial q}{\partial z^*} \cdot \frac{\partial z^*}{\partial \sigma} + \frac{\partial q}{\partial \sigma},$$

There exist two competing forces:

On the one hand, the bank would deleverage to decrease the default rate. Volatility increase would have a negative impact on default cutoff  $z^*$ , imposing a positive impact on the bond price:

$$\therefore \frac{\partial q}{\partial z^*} = -\frac{1}{1+r} \left[ f(z^*)(1-\theta) + \int_0^{z^*} \frac{z\theta}{z^{*2}} dF(z) \right] < 0,$$

and from Proposition 2,  $\frac{\partial z^*}{\partial \sigma} < 0$ ,

$$\therefore \frac{\partial q}{\partial z^*} \cdot \frac{\partial z^*}{\partial \sigma} > 0.$$

On the other hand, the increase of volatility would increase the default rate for any given default cutoff, this would have a negative impact on bond price.

The sign of  $\frac{dq}{d\sigma}$  depends on which force prevails. Under lognormal distribution, it can be shown that the second force prevails.

After some algebra, it can be shown that, under assumption 1,  $z^* e^{-\frac{[\sigma^4 - 2\log(z^*)^2]}{8\sigma^2}} \operatorname{erfc}(\sqrt{\pi}) < \operatorname{erfc}(\sqrt{\pi}) < \theta$ , thus:

$$\frac{dq}{d\sigma} = -a_2 \left\{ \left[ \theta - z^* e^{-\frac{[\sigma^4 - 2\log(z^*)^2]}{8\sigma^2}} \operatorname{erfc}(\sqrt{\pi}) \right] \sigma^2 - \left[ 2\theta + z^* e^{-\frac{[\sigma^4 - 2\log(z^*)^2]}{8\sigma^2}} \operatorname{erfc}(\sqrt{\pi}) \right] \log(z^*) \right\} < 0$$

where  $a_2 = \frac{1}{2z^* \sqrt{2\pi}\sigma^2} e^{-\frac{[\sigma^4 - 2\log(z^*)^2]}{8\sigma^2}} > 0$

Denote  $spread = \frac{1}{q} - 1 - r$ , then  $\frac{\partial spread}{\partial \sigma} = -\frac{1}{q^2} \frac{dq}{d\sigma} > 0$

<sup>41</sup>Notes that since both asset size  $k$  and leverage  $z^*$  are decreasing in  $\sigma$ , when  $\sigma$  increases, the asset and leverage ratio both decreases. This prediction is consistent with the empirical observation.

Q.E.D

## D Data

I now describe in detail how I obtain the data for shadow banks. In the literature, shadow banks are often defined as financial institutions that do not have access to central bank liquidity or public sector credit guarantees. One of the difficulties for analyzing shadow banking is the lack of publicly available micro-level dataset. Another difficulty lies in the fact that the definition of shadow banks is not clear-cut. Commercial banks also engage in shadow banking activities and many shadow banking activities are not reported on the banks' balance sheets. In this paper, I obtain the yearly bank-level panel data from the BankScope database, complemented with bank-level data from WorldScope database. BankScope and WorldScope database contain comprehensive information on banks across the globe. I choose real estate and mortgage banks, investment banks, micro-financing institutions, securities firms, private banking and asset management companies, investment and trust corporations, finance companies, group finance companies of U.S. as representatives of shadow banks. I also choose commercial banks, savings banks, cooperative banks, and bank holding companies as representatives of traditional banks. I drop all banks which have negative equity/asset/capital or deposits, drop all banks with faulty records such as inconsistent information on any generic variables: date of establishment/type of company etc. The variables I am interested in are: assets, liabilities, return on asset(ROA), long-term asset, short-term asset, deposit, equity, derivatives, other securities. The final panel data sample contains 281 shadow banks and 9554 traditional banks from 1998 to 2013, covering 49 states of the U.S.